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Latest research trends in gait analysis using wearable sensors and machine learning

A systematic review

Saboor, Abdul; Kask, Triin; Kuusik, Alar; Alam, Muhammad Mahtab; Le Moullec, Yannick; Niazi, Imran Khan; Zoha, Ahmed; Ahmad, Rizwan

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Latest Research Trends in Gait Analysis Using Wearable Sensors and Machine Learning: A Systematic Review

ABDUL SABOOR¹, TRIIN KASK¹, ALAR KUUSIK¹, (Member, IEEE),
MUHAMMAD MAHTAB ALAM¹, (Senior Member, IEEE),
YANNICK LE MOULLEC¹, (Member, IEEE), IMRAN KHAN NIAZI^{2,3,4}, (Senior Member, IEEE),
AHMED ZOHA⁵, (Member, IEEE), AND RIZWAN AHMAD⁶, (Member, IEEE)

¹Thomas Johann Seebeck Department of Electronics, Tallinn University of Technology, 12616 Tallinn, Estonia

²Center of Chiropractic Research, New Zealand College of Chiropractic, Auckland 1149, New Zealand

³Health and Rehabilitation Research Institute, AUT University, Auckland 1010, New Zealand

⁴Department of Health Science and Technology, Aalborg University, 9100 Aalborg, Denmark

⁵James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, U.K.

⁶School of Electrical Engineering and Computer Science, National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan

Corresponding author: Abdul Saboor (abdul.saboor@taltech.ee)

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ABSTRACT Gait is the locomotion attained through the movement of limbs and gait analysis examines the patterns (normal/abnormal) depending on the gait cycle. It contributes to the development of various applications in the medical, security, sports, and fitness domains to improve the overall outcome. Among many available technologies, two emerging technologies that play a central role in modern day gait analysis are: A) wearable sensors which provide a convenient, efficient, and inexpensive way to collect data and B) Machine Learning Methods (MLMs) which enable high accuracy gait feature extraction for analysis. Given their prominent roles, this paper presents a review of the latest trends in gait analysis using wearable sensors and Machine Learning (ML). It explores the recent papers along with the publication details and key parameters such as sampling rates, MLMs, wearable sensors, number of sensors, and their locations. Furthermore, the paper provides recommendations for selecting a MLM, wearable sensor and its location for a specific application. Finally, it suggests some future directions for gait analysis and its applications.

INDEX TERMS Gait analysis, machine learning, wearable sensors, survey, medical applications.

I. INTRODUCTION

Walking is a fundamental human activity that involves the combined efforts of the muscles, brain and its nerves [1]. Gait refers to cyclical locomotion achieved through walking. This includes the movements of arms, legs, hip, feet, and limbs [2]. Generally, the gait of each person is unique depending on the gait parameters such as gait phases, step length and muscle force, etc., [3]. Therefore, it helps to understand the individuality and liberty in humans. The analysis and characterization of gait parameters is called gait analysis. Gait analysis helps in investigating different musculoskeletal functions and

gait parameters. Therefore, gait analysis supports numerous applications in healthcare [4]–[8], security [9]–[11], sports and fitness domains [12], [13]. For example, Hu *et al.* [4] provide a vision-based solution for the Freezing of Gait (FoG) detection. Similarly, [5], [6] and [8] are gait based assessment solutions for Parkinson Disease (PD), cerebral palsy and variety of chronic diseases progression, respectively. Gait analysis requires data acquisition and extraction tools of the gait features. For gait analysis and feature extraction, various wearable and non-wearable solutions are proposed in the literature. Non-wearable methods generally consist of vision-based, environment-based, Radio Frequency (RF) based solutions. In contrast, wearable technologies are composed of accelerometer, gyroscope and force sensors, etc.

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TABLE 1. List of important acronyms.

Acronym	Extended Meaning
Acc	Accuracy
ADL	Activities of Daily Life
ANN	Artificial Neural Networks
AdaBoost	Adaptive Boosting
BAC	Blood Alcohol Content
CheC	Chebyshev Classifiers
CNN	Convolutional Neural Network
CART	Classification And Regression Trees
DAS	Distributed ASCII Supercomputer
DBN	Deep Belief Network
DCWRNN	Dense Clock Wise Recurrent Neural Network
DA	Discriminant Analysis
DT	Decision Tree
EMG	Electromyography
ERT	Extremely randomized tree
FPN	False Positive or Negative
FFT	Fast Fourier Transform
FoG	Freezing of Gait
FEC	Functional Electrical Stimulators
GSR	Galvanic Skin Re-sponse
GAN	Generative Adversarial Network
GRF	Ground Reaction Force
HAR	Human Activity Recognition
IMU	Inertial Measurement Unit
KAM	Knee Adduction Movement
KNN	K-Nearest Neighbors
LR	Logistic Regression
LSTM	Long Short-Term Memory
LDA	Linear Discriminant Analysis
MAE	Mean Absolute Error
MRF	Markov Random Field
MEMS	Micro-Electro-Mechanical Systems
ML	Machine Learning
MLM	Machine Learning Method
MLP	Multilayer Perceptron
MS	Multiple Sclerosis
PCA	Principal Component Analysis
PD	Parkinson Disease
Pre	Precision
RF	Radio Frequency
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
Sen	Sensitivity
Spe	Specificity
SAE	Stacked Auto Encoder
SVC	Support Vector Clustering
SVM	Support Vector Machine
SVR	Support Vector Regression
WiFi	Wireless Fidelity

Vision-based gait analysis use either a video camera [14], [15], a thermal vision sensor [16], [17] or a depth camera [18], [19]. Alternatively, the environment-based gait assessment rely on floor-deployed pressure sensors [20], [21] and infrared sensors [22], [23]. However, both such solutions require a controlled research facility for the analysis that limits their applicability in external/outdoor environments [24]. RF-based solutions are made of radars [25], [26], other microwave sensors [27] and Wireless Fidelity (WiFi) beacons [28], [29], and suffer from the complexity involved in installation. In contrast, wearable sensor solutions are cheap and can be used outside controlled environments while the user is performing daily activities naturally. Wearable sensors are worn or attached to various parts of the body to monitor vitals

and gait parameters. Therefore, wearables are frequently considered as the the most suitable technology for the healthcare, security, sports, and fitness applications [30]–[32]. In gait analysis, accelerometers [33], [34], gyroscopes [35], Inertial Measurement Units (IMUs) [36] and force sensors [37] are widely used to measure gait characteristics [38]. For example, Derawi *et al.* [33] measure the cycle length using a hip-worn accelerometer for gait based authentication. Similarly, a gyroscope attached to the trunk is used to monitor the change in the trunk angle for fall detection in [35].

Different sensors enable collecting a lot of data for gait analysis; then, the challenge is that data processing and learning algorithms are required to make decisions. For example, the decision to stimulate the muscles based on irregular gait for fall prevention. Threshold-based statistical solutions are widely used for such processing. Additionally, it helps in analyzing the effects of various independent gait variables on dependent gait variables. Multivariate statistical techniques such as Linear Discriminant Analysis (LDA) and Principle Component Analysis (PCA) help in representing the gait data for linear analysis [39]. Similarly, such methods reduce the dimensionality of the data. However, these approaches often generate a high number of false alarms during gait classification. The statistical approaches produce less efficient results when the nature of the problem is nonlinear or complex [40]. One more drawback of employing statistical methods for the gait analysis is their sensitivity to noisy data that leads to performance degradation [41]. Therefore, the latest research is moving towards Machine Learning (ML) because of high accuracy in processing the gait parameters based on application requirements [42].

TABLE 1 lists the important acronyms and TABLE 2 provides an overview of the target areas and limitations of the existing reviews. Tao *et al.* [43] provide a detailed review of the gait analysis and wearable sensors. Similarly, [24] presents a review of gait analysis using wearable and non-wearable systems. However, both studies are relatively old (2012 and 2014) and do not include the Machine Learning Methods (MLMs). Likewise, [44] presents a systematic review of gait analysis and wearable sensors but is not specific to ML. The studies [45], [46] provide reviews on accelerometer-based gait analysis and inertial sensor-based gait analysis, respectively. However, there are various other wearable sensors such as gyroscope, pressure sensor, etc., which are not covered in such reviews. Reviews on gait based recognition (identifying a person based on walking pattern) are given in [47], [48]. However, these studies are specific to the security applications of gait analysis and are not purely based on wearable sensors and ML. The papers [49], [50] are specific to deep learning approaches for security and healthcare using gait analysis. Similarly, a survey on gait analysis limited to fall detection and fall prevention is presented in [51]. A broader review of human gait analysis along with approaches, applications, and ML is provided in [40].

In contrast to the above works, we present a survey specific to wearable sensors combined with ML to highlight the latest

trends in the domain of gait analysis. The reason for selecting these technologies is their ability to develop environment-independent and realistic applications. The overall contributions of this paper are listed as follows:

- It provides an overview of gait analysis and wearable sensors for gait analysis.
- It provides a review of the latest research trends in gait analysis using wearable sensors and ML. The review includes an overview of selected papers, publication details, MLMs, and key parameters of selected papers.
- It summarizes the key insights from the state of the art research studies and identify gaps and opportunities to further advance the research.
- It highlights the applications of gait analysis and recommends (based on analysis) the optimal (widely used) MLM, wearable sensor, and its location for a specific application.
- It presents the relationship between sample size and application based on the analysis.
- It highlights the future research directions for the researchers working in the domain of gait analysis.

The rest of the paper is organized as follows. Section II explains the methodology for paper selection. Gait analysis along with its applications are introduced in Section III. Section IV describes the wearable sensors for gait analysis. A comprehensive review of the selected papers is presented in Section V. Finally, Section VI and Section VIII provide the future directions and conclusion of the work, respectively.

II. METHOD

For the systematic review and analysis, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method is used [52]. The paper selection method based on PRISMA is illustrated in figure 1 and summarized in what follows.

The PRISMA method is based on four steps as given below:

- 1) Identification
- 2) Screening
- 3) Eligibility Checking
- 4) Selection

The identification process involves the recognition of articles for this systematic literature review. Therefore, we have explored following scientific libraries: Google Scholar, PubMed, IEEE Xplore, and Science Direct for paper identification and selection. Multiple data strings have been used to search papers in different libraries as shown in TABLE 3.

The identification process using the above-mentioned strings resulted in more than 5000 documents. During the identification process, only the papers from 2015 onward were considered as we aim to highlight the latest trends in this domain. In the initial screening, a total of 754 papers were shortlisted based on their title by 31st January, 2020. All these papers were further processed based on their abstract, conclusion, and language, reducing the number of papers to

272. In the eligibility check phase, these papers were down-loaded and a critical selection criterion is performed based on the full-text read. The parameters for eligibility check are:

- The published paper should be a journal article or a conference paper;
- The published paper should deal with gait analysis;
- The published paper should include MLMs;
- The published paper should use wearable sensors for data acquisition. Hence, all the vision-based papers were removed;
- The paper should present a concrete methodology and results.

Finally, after performing the above-mentioned steps and removing 21 duplicate papers, we were left with 33 papers which have been selected for this review. However, it is important to provide an overview of gait and wearables before reviewing the selected papers. Therefore, the next two sections provide the details of gait and wearables.

III. GAIT ANALYSIS

Gait is the periodic movement of hands and feet [53]. Different gait patterns are distinguished by differences in velocity, limb movements, force, and ground contact duration. Gait analysis is the study of gait (for example human) using visual assessment, and instruments such as cameras and sensors [54]. It accesses the walking condition of an individual that is beneficial for designing various applications in medical, security, sports, and fitness domain [55]–[59]. The overall gait is divided into several phases that result in defining the walking pattern. It is important to understand the functionality of each stage to identify the changes in normal gait precisely. Therefore, section III-A presents an overview of the gait phases.

A. GAIT PHASES

A gait cycle is defined as the duration between the consecutive strikes of the same foot during human locomotion. The overall gait cycle is divided into two major phases, as shown in Figure 2:

- 1) **Stance Phase:** In this phase (Figure 2(1)), the foot remains in contact with the ground. This phase contributes to the 62% of the gait cycle [60]. The Stance phase is further divided into 5 phases.
 - Initial Contact
 - Loading Response
 - Mid Stance
 - Terminal Stance
 - Pre-Swing
- 2) **Swing Phase:** In this phase (Figure 2(2)), the foot remains in the swing position without the contact of ground. This phase contributes to 38% of gait cycle. The swing phase is subdivided in three phases.
 - Initial Swing
 - Mid Swing
 - Terminal Swing

TABLE 2. Overview of key parameters.

Name	Year	MLMs	Wearable Sensor	Target Area(s)	Limitation(s)
Gafurov et al. [48]	2007	✗	✓	<ul style="list-style-type: none"> Gait analysis for biometric Gait analysis using wearables and non-wearables Challenge and strengths of gait analysis for security 	<ul style="list-style-type: none"> Specific to security applications of gait analysis Missing the analysis of state of the art studies Old Literature (Covering the studies older than 2007) Lacking the explanation of sensors
Tao et al. [43]	2012	✗	✓	<ul style="list-style-type: none"> Gait analysis using wearable sensors Wearables for gait analysis Applications of gait analysis using wearables 	<ul style="list-style-type: none"> Old Literature (Covering the studies older than 2012) MLMs are not covered Missing the analysis of state of the art studies
Muro-de-la-Herran et al. [24]	2012	✗	✓	<ul style="list-style-type: none"> Gait analysis using wearable and non-wearable sensors Gait parameters and applications Comparison of wearable and non-wearable sensors Analysis of wearable and non-wearable sensors 	<ul style="list-style-type: none"> Old Literature (Covering the studies older than 2014) MLMs are not covered Missing the analysis of state of the art studies
Sprager et al. [46]	2015	✓	✓	<ul style="list-style-type: none"> Gait analysis using inertial sensor Layout of inertial sensor based gait recognition approaches Specification and overview of inertial based schemes Analysis of impacts provided by recent studies such as performance, collectability, applicability and security 	<ul style="list-style-type: none"> Specific to inertial sensor based gait analysis
Continued on next page					

TABLE 2. (Continued.) Overview of key parameters.

Name	Year	MLMs	Wearable Sensor	Target Area(s)	Limitation(s)
Chen et al. [44]	2016	X	✓	<ul style="list-style-type: none"> Gait analysis using wearable sensors Gait parameters and applications Methods for gait feature extraction such as wearables, nonlinear analysis techniques, kinetics and muscle activity 	<ul style="list-style-type: none"> Specific to clinical applications Missing the analysis of state of the art studies Lacking the explanation of wearable sensors MLMs are not covered
Wan et al. [47]	2018	✓	✓	<ul style="list-style-type: none"> Gait analysis and its framework for recognition Data acquisition methods (vision-based, sensor-based) Feature representation, dimension reduction and vulnerabilities of gait-based biometrics Analysis of recent studies 	<ul style="list-style-type: none"> Specific to security applications of gait analysis
Meena et al. [40]	2018	✓	✓	<ul style="list-style-type: none"> Recent developments in human gait Parameters in gait analysis Wearable and non-wearable techniques in gait MLMs for gait analysis Analysis of the state of the art papers 	<ul style="list-style-type: none"> Focusing mainly on vision based technologies for gait analysis. Therefore, it only includes twelve studies based on wearable sensors and MLMs. Majority of wearable and ML based studies are older. For example, 6 out of twelve studies are older than 2010. Similarly, all the studies based on the above-mentioned criteria are older than 2015
Costilla-Reyes et al. [49]	2019	✓	✓	<ul style="list-style-type: none"> Deep learning for security and healthcare Analysis of wearables and non-wearables Overview of deep learning techniques Case studies of deep learning in security and healthcare 	<ul style="list-style-type: none"> Lacking the details of potential applications in healthcare and fitness. Missing the analysis of state of the art studies Not entirely focusing on gait
Continued on next page					

TABLE 2. (Continued.) Overview of key parameters.

Name	Year	MLMs	Wearable Sensor	Target Area(s)	Limitation(s)
Wang et al. [50]	2019	✓	✓	<ul style="list-style-type: none"> • Deep learning and sensor based activity recognition • Overview of deep learning and challenges • Analysis of the state of the art studies • Overview of publicly available datasets 	<ul style="list-style-type: none"> • Focus is limited to the Human Activity Recognition (HAR) • Not entirely focusing on gait
Ren et al. [51]	2019	✓	✓	<ul style="list-style-type: none"> • Review on fall detection and prevention • Classification of fall detection and prevention systems • Analysis of the recent papers based on wearable and non-wearable technologies 	<ul style="list-style-type: none"> • Limited to fall detection and prevention • Not entirely focusing on gait
This Paper	2020	✓	✓	<ul style="list-style-type: none"> • Gait analysis using wearable sensors and MLMs • Gait parameters and applications based on gait parameters • Overview of wearables for gait analysis • Overview and analysis of recent state of the art studies • Recommendations for MLM, wearable and its location for particular application based on its usage in literature • Future research directions in the domain of gait analysis and its applications 	<ul style="list-style-type: none"> • Focusing only on wearables and ML for gait analysis and its applications

Initial Contact:

In this phase, the heel strikes the ground and initiate the joint loading response pattern. The initial contact makes 0-3% of the overall gait cycle.

Loading Response:

This phase covers 3-12% of the gait cycle that includes the flat foot placement on the ground. It allows flexion in the knee for shock absorption. This phase starts after the initial contact and remains until the opposite foot is raised for the swing.

Mid Stance:

In this phase, the shank moves forward to support the forward foot propulsion. It constitutes a 12-31% portion of the gait cycle. The mid stance phase starts from the lifting of the opposite foot and continues until the bodyweight is aligned to the forefoot.

Terminal Stance:

It makes 31-50% of the overall gait cycle and starts with the rise of the heel from the ground. It lasts until the opposite foot strikes the ground. This is the final phase in which the single-limb supports the movement. Also, the bodyweight moves ahead of the forefoot in this phase.

Pre-Swing:

It is the final sub-phase of the stance that consists of 50-62% of the overall gait cycle. This phase acts as a transition between the stance and swing phase. It starts with the initial contact of the opposite limb and remains until the toe-off of the first foot.

Initial Swing:

Initial swing is the first stage of the swing phase that covers 62-75% of the gait cycle [60]. It starts with the rise of the foot from the ground and lasts until the swing foot is opposite to the stance foot. It causes a flexion in the knee and ankle, causing the clearance of the foot over the ground.

Mid Swing:

The mid-swing covers 75-85% of the gait cycle. During this phase, the thigh reaches its maximum advancement by continuing the limb advancements. This phase starts after the initial swing phase and remains until the hip and knee flexion postures become equal.

Terminal Swing:

The final phase of the gait cycle makes 85-100% of the overall cycle. This phase completes the limb advancement through knee extension. At the end of this phase, the foot goes in the state of initial contact.

Each phase follows a unique sequence of motion to reach the motion objective. Therefore, these phases facilitate the design of various applications in the domain of medical, sports, and security. An overview of different gait patterns useful for the specific applications is presented in TABLE 4 [24] and a tree diagram of the sub-categories of gait based applications is presented in Figure 3. Gait phases in one cycle are determined by algorithms mostly for generating a user-specific gait template. This is specifically important in wearables designed for the elderly. The biggest challenges

TABLE 3. Strings used in search engines of academic literature databases.

Academic Library	Search String
Google Scholar	<ul style="list-style-type: none"> • Gait Analysis • Gait Analysis using Machine Learning • Gait Analysis Applications • Gait Analysis for Rehabilitation • Gait Analysis for Clinical Purpose • Activities of Daily Life Using Gait and Machine Learning • Injury Avoidance and Machine Learning • Fall Prevention Using Gait • Fall Prevention Using Machine Learning • Condition Assessment With Gait • Sensors and Machine Learning For Gait Analysis • Gait Analysis Using Wearable Sensors • Wearable Sensors and Activities of Daily Life • Gait Analysis For Sports and Fitness
PubMed	<ul style="list-style-type: none"> • Gait[Title/Abstract] AND Analysis[Title/Abstract] OR Machine Learning[Title/Abstract] AND ("2015/01/01"[PDAT] : "2020/03/01"[PDAT]) • Machine Learning[Title/Abstract] AND Sensors[Title/Abstract] OR Gait [Title/Abstract] AND ("2015/01/01"[PDAT] : "2020/03/01"[PDAT]) • Gait Analysis[Title/Abstract] AND Applications[Title/Abstract] OR Machine Learning [Title/Abstract] AND ("2015/01/01"[PDAT] : "2020/03/01"[PDAT])
IEEE Xplore	<ul style="list-style-type: none"> • (((("All Metadata":Gait) AND "All Metadata":Sensors) OR "All Metadata":Machine Learning) //Filters Applied: 2015 – 2020 • (((("All Metadata":Machine) AND "All Metadata":Learning) OR "All Metadata":Gait Analysis) //Filters Applied: 2015 – 2020 • (((("All Metadata":Gait Analysis) OR "All Metadata":Sensors) OR "All Metadata":Applications) //Filters Applied: 2015 – 2020 • (((("All Metadata":Sensors) AND "All Metadata":ADL) OR "All Metadata": Machine Learning) //Filters Applied: 2015 – 2020
Science Direct	<ul style="list-style-type: none"> • "Gait Analysis" and Machine Learning or Sensors. Limited to research articles, conference abstracts • "Gait Analysis" and Applications. Limited to research articles, conference abstracts • "Machine Learning" and Gait or applications. Limited to research articles, conference abstracts

in gait template generation is the adaptability of algorithms when gait speed changes. That is why it is recommended that at least 3 different algorithms are used when generating such template (third as a fallback algorithm) [61]. The splasticity of algorithms used is mostly affected by the wearer's age. Young adults (aged 20-30) have more consistent walking pattern and gait symmetry while individuals older than 50 have shown to exhibit left-right gait asymmetry and lack of gait consistency. It is also hard for the algorithms used to detect phase transitions [62].

Correct gait phase detection is important especially in medical applications (both temporal and spatial gait parameters) because they allow disease and/or traumatic event assessment and provide data for physical therapy for treatment optimization. Gait analysis in wearables are used for example with

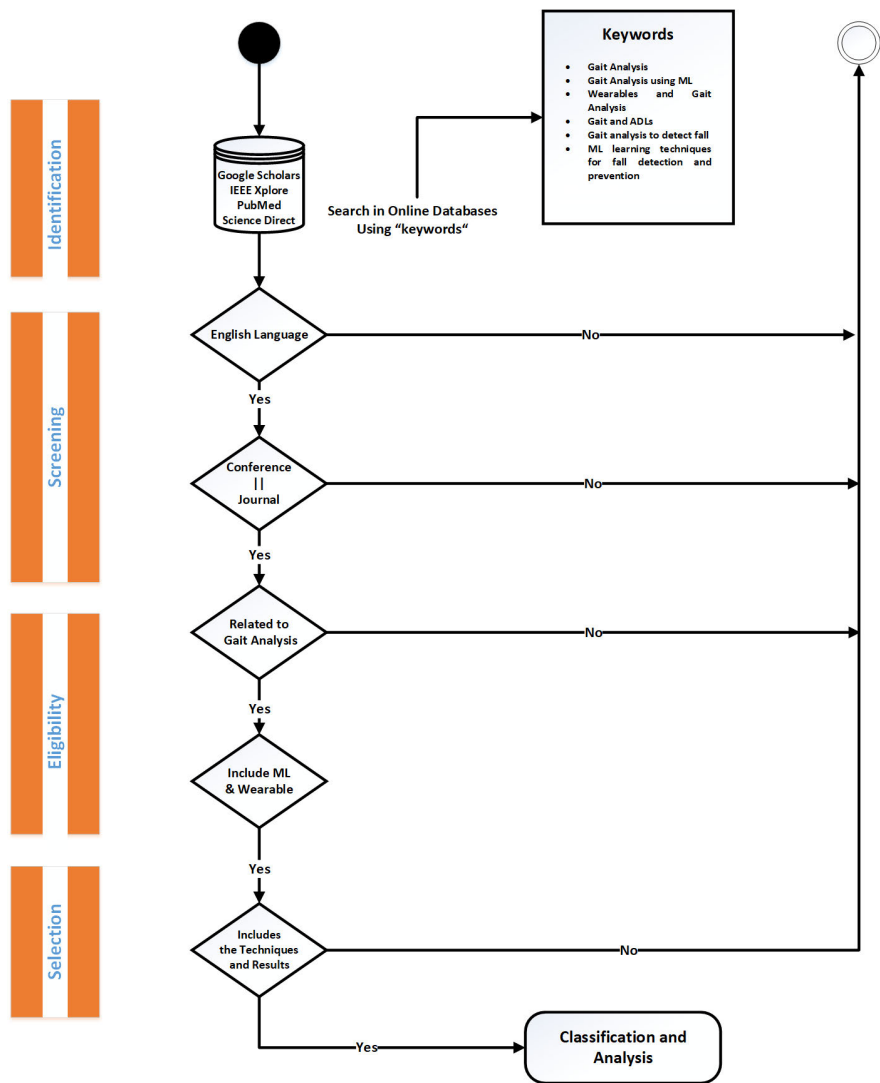


FIGURE 1. PRISMA flow diagram for paper selection.

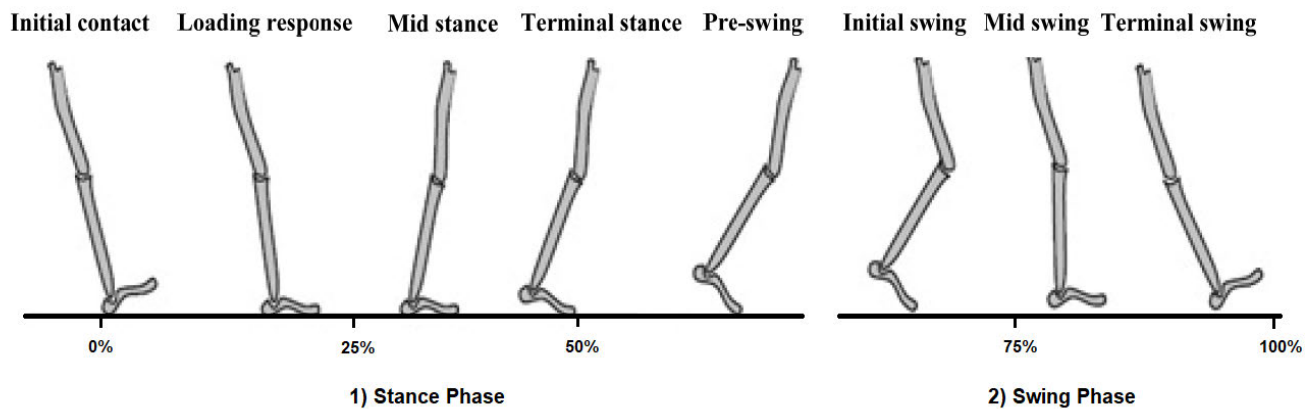


FIGURE 2. Gait phases in a normal gait cycle. (a) Stance phase; (b) Swing phase [43].

stroke patients or patients with underlying neurodegenerative disease (such as Multiple Sclerosis (MS)). For MS gait cycle-based control of Functional Electrical Stimulators (FES) for drop foot compensation is the main application. In more

general cases, spatial gait parameter such as stride length can be used to detect a fall [63]. As mentioned in Section I, we are only considering the gait analysis techniques based on wearable sensors. Therefore,

Section IV provides an overview of the wearable sensors used for gait analysis.

TABLE 4. Gait parameters and applications.

Gait Parameter	Medical	Fitness	Security
Body Posture	✓	✓	✓
Covered Distance	✓	✓	
Fall	✓	✓	
Gait Phases	✓	✓	✓
Joint Angle	✓	✓	
Momentum	✓	✓	
Muscle Force	✓	✓	
Stance Time	✓		
Step Angle	✓	✓	✓
Step Length	✓	✓	✓
Step Time	✓		
Step Width	✓	✓	✓
Stride Length	✓	✓	✓
Stride Velocity	✓	✓	✓
Swing Time	✓		
Rhythm	✓	✓	✓

IV. WEARABLE SENSORS FOR GAIT ANALYSIS

There exist various technologies for gait human analysis such as marker and marker-less vision-based technologies, radio emission and reflection based technologies for mobility (localization beacons) and motion speed (Doppler radar) assessment, and wearable motion sensors. Vision-based sensors require an infrastructure setup for analysis [24]. Therefore, this solution is intrusive for Activities of Daily Life (ADL) monitoring and gait support scenarios. Besides, the setup required for vision-based motion analysis is expensive. Radio emission sensors lack precision for high resolution gait analysis and also require supporting infrastructure. Thus, we shall only consider wearable (motion) sensors in this review because of practical use aspects. The history of wearable sensors starts in the 15th century with the development of watches. But, the actual rise in this domain begins in the 19th century. For example, a wearable camera was developed in 1907 for pigeon photography. Similarly, Galvanic Skin Response (GSR) was invented before world war II to detect the lie using pulse rate and blood pressure. After that, numerous wearable sensors were developed, such as accelerometer, gyroscope and force sensors, etc. Generally speaking, wearable sensors are lightweight, cheap, and can be used to collect the data without disturbing the daily life activities [64]. The same sensors are widely integrated into handheld and smartphone devices, making possible smartphone-based human motion assessment. The overall specifications of widely used wearable sensors (as shown in Figure 4) in gait analysis are presented in the following:

A. ACCELEROMETER

Wearable accelerometers used today are virtually exclusively based on triaxial Micro-Electro-Mechanical Systems (MEMS) relying on capacitance change measurements [65]. Typical resolution of accelerometers of wearable devices is 14-16 bits and the full scale acceleration is 20-160 m/s².

Among the other MEMS motion sensors accelerometers have the lowest energy consumption of some tens of microwatts in average. Due to the fact that accelerometer also measures the gravity it can be well used for the absolute orientation detection and Zero velocity UPDate (ZUPD) of gait phasing [66]. From the other side, linear displacement calculation requires double integration of the accelerometer output signal. Physical sensor nonlinearities cause a bias error that will quickly accumulate without appropriate compensation of ZUPD or other methods and is the main obstacle of precise dead reckoning motion tracking. Finite sampling rate also causes motion measurement errors proportional to the speed and duration of fast movements. Fortunately, modern wearable MEMS accelerometers provide sampling rate of up to 1 kHz that is exceeding the measurement rate used by the majority of gait analysis experimenting researchers.

B. GYROSCOPE

A gyroscope is also a triaxial MEMS device measuring the angular velocity of an object, i.e. body part [67]. A gyroscope works on the Coriolis principle in which the angular momentum is measured based on the linear motion [68]. Typical resolution and sampling rate of modern gyroscopes is similar to accelerometers, maximum angular speed is around 1000-2000 degrees per second; energy consumption is an order of magnitude higher. Gyroscope sensors can be placed on different parts of the human body such as foot, ankle, knee, and waist allowing to identify the human posture and gait phases [69]. The benefits of gyroscopes compared to accelerometers are smaller bias drift and measurements insensitivity to shocks and gravity field impact.

C. MAGNETOMETER

The magnetometer measures the direction, strength, and relative change of a magnetic field [70]. In the context of wearables, Earth's magnetic field is observed relying on Hall effect. Magnetometers can be beneficial in measuring the absolute orientation of a subject for gait analysis [43]. The sampling rate and Signal to Noise Ratio (SNR) resolution of micromechanical magnetometers tends to be lower, 10-100Hz and 8-12 bits respectively. Therefore magnetometers are used as assistive motion sensor components.

D. COMBINED IMU

IMU is a combined sensor device that measures the linear acceleration, angular speed, (absolute) orientation, and gravitational force of a subject using the combination of linear accelerometer, gyroscope, and magnetometer [71]. Typically, Mahony filter with a supplemental Kalman filter is used for physical sensor fusion of triaxial IMU devices [72]. Some devices, i.e. Bosch Sensortec chips directly output absolute orientation in quaternions with the update rate of 100Hz. Because of its tiny size and internal sensor fusion implementation, the IMU is the most popular and precise wearable sensor type for developing gait analysis applications [73].

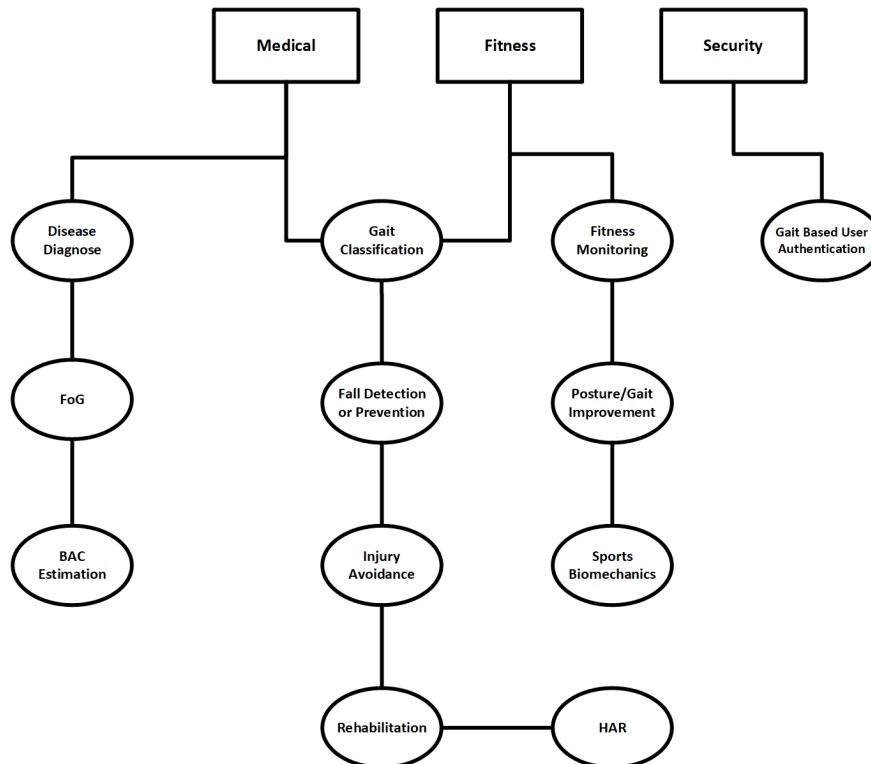


FIGURE 3. Common applications of gait analysis.

E. BAROMETER

MEMS barometers (altimeters) are also used additionally to IMU devices. Such sensors output altitude information and are used for detecting up- or downstairs movements. However, barometric sensors are rarely deployed for gait analysis due to rather slow reaction and inaccuracy.

F. FORCE AND STRAIN SENSORS

Force or pressure sensing is used in robotics, haptic sensing including interactive toys, medical devices [74]–[76]. The force sensors are divided into four main types: capacitive force sensors, piezoelectric force sensors, resistive, and optical fibre bragg grating force sensors. The pressure force sensor is widely used for gait analysis from simple by embedding them in the shoes or soles [24]. In such case sensor measures the Ground Reaction Force (GRF) [77]. By a simple case a single force sensor is used for gait phase separation, for example on foot-drop electrical stimulation devices. In sophisticated cases whole pressure map of the footstep is derived by the sensor. Sensoria footwear can be mentioned as a typical commercial example here. Force (strain) sensors are also used as goniometers for joint angle measurements [78]. There is a tendency to move towards textile-based stretching strain sensors [79]. Xenoma e-skin strain sensitive garment is a typical product example of such sensors.

G. ELECTROMYOGRAPHY (EMG)

An EMG measures muscle activities such as the voluntary or involuntary contraction of muscles [80]. It can dis-

close muscle dysfunction, nerve dysfunction, and transmission problems between the nerve and muscle all causing gait impairments [81]. EMG electrodes of the sensor capture electrical signals used for muscle contraction [82]. After acquisition, these signals can be further analyzed to detect abnormalities. The EMG sensor uses two types of electrodes: needle-like invasive electrodes for high dept and high sensitivity measurements and non-invasive less sensitive skin surface electrodes [83]. The surface EMG (sEMG) testing offers an assessment of various gait-related features like changes in muscle properties paresis and muscle stiffness and tension [24].

Along with the above-mentioned wearables, there exist various other wearable sensors with applicability in gait analysis such as electromagnetic tracking system (ETS) [43].

Nowadays, many studies are focusing on combining the data of multiple sources as a sensor data fusion to improve the performance of gait analysis. The sensor fusion could be divided into homogeneous and heterogeneous solutions [84], [85]. Homogeneous sensor fusion combines data from the same type of sensors such as wearable-wearable, while heterogeneous sensor fusion merges data from different sensor types like wearable-vision. The performance of gait analysis is highly dependent on the underlying algorithms for the analysis. Generally, different gait-based human activities such as lying down, falling, jogging, and running are closely related. The statistical approaches find it hard to classify such activities accurately, especially noisy, nonlinear, and complex data. The MLM proves to be an excellent alternative

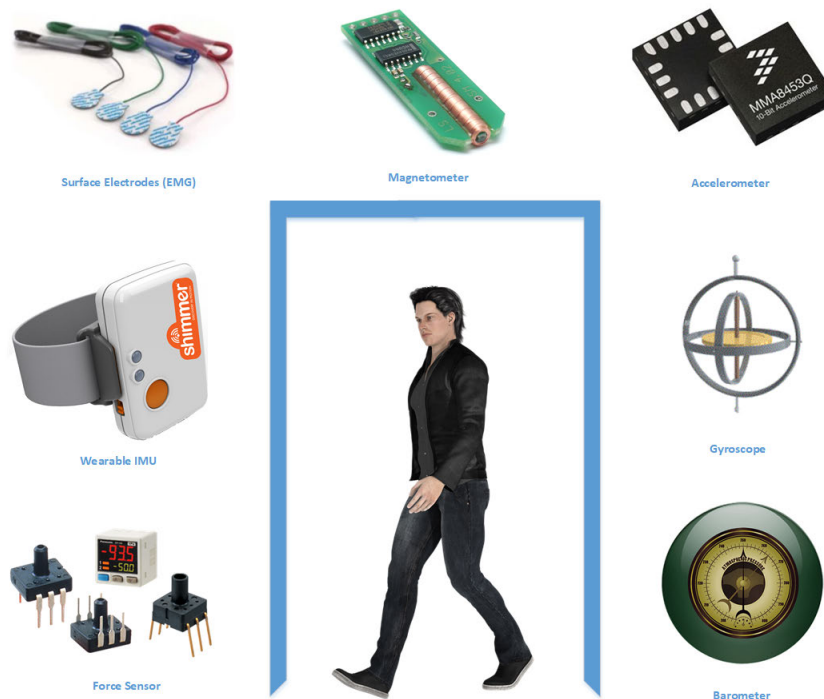


FIGURE 4. Examples of wearable sensors for gait analysis.

to provide high classification accuracy of gait parameters. Therefore, we have only explored the MLMs in this review. The comprehensive survey of gait analysis techniques based on wearable sensors and MLMs is presented in next Section.

V. NARRATIVE REVIEW ON GAIT ANALYSIS USING WEARABLE SENSORS AND ML

The aim of this paper is to present and analyse the recent trends in gait analysis based on wearables and machine learning. Therefore, as mentioned earlier in Section II, a total of 33 papers have been selected for the period 2015 to 2020. A general overview of the selected papers along with key findings and limitations is presented in Subsection V-A. This is followed by a qualitative synthesis in Subsection V-B.

A. OVERVIEW OF SELECTED PAPERS

Wu and Wu [86]:

This paper aims the accurate identification of the gait. Each participant performs a 10 m walk carrying a force plate at the foot for data acquisition. The data values are further normalized based on body weight and duration of gait. The gait variability of six gait parameters is analyzed using the coefficient of variation. Support Vector Machine (SVM) [87] is used to evaluate the gait symmetry in this study. The analysis is done using three different kernel types (Linear, Polynomial, Gaussian Radial Basis Function) in SVM for each dataset [88]. A 101-dimensional gait pattern is used for SVM training. Finally, a six-dimensional cross-validation scheme was proposed to evaluate the performance of SVM.

Key Findings:

The classification performance of SVM is maximum when the gait parameters are obtained using PCA. The PCA

removes the redundant gait information that results in obtaining accuracy (90%), sensitivity (90%), and specificity (88%). These results are better than using a 101-dimensional gait pattern (in which PCA is not used) with accuracy (87%), sensitivity (86%), and specificity (85%). The second key finding of this study is SVM with a non-linear kernel obtains better intrinsic information hidden in gait parameters than SVM with a linear kernel.

Limitations:

The authors use statistical learning algorithms to quantify gait symmetry. However, statistical symmetry measures are computationally expensive, and their explication is less clear than discrete approaches.

Chen and Xue [89]:

This paper aims the recognition of different human activities using sensors. A mobile-based accelerometer is used to acquire data from subjects while performing eight different ADL. Additionally, an android based application is developed to facilitate the data acquisition method. A modified CNN that works on selecting the best number of epochs is used for activity recognition. It includes three convolution layers and three pooling layers. During this study, the width of the convolutional kernel is set to two. The suggested CNN shows better accuracy results than SVM and an 8-layer Deep Belief Network (DBN) [90].

Key Findings:

The paper shows that CNN offers the highest HAR accuracy (93.8%) as compared to SVM (90%) and DBN (88%). One more finding is that both the SVM and DBN show better recognition accuracy when combined with FFT during the extraction process. Lastly, the average accuracy of CNN is

minimum (88.3%) during walking identification as compared to falling, running, walking quickly, etc. This is because of walking is sometimes confused with quick walking and walking up/downstairs.

Limitations:

The proposed solution applies CNN to the entire dataset of the sensor. It impacts the computational power and introduces energy inefficiency for the mobile wearable device [91].

Zebin *et al.* [92]:

This paper's aim is the activity recognition of six different and common daily life activities. In the study, five inertial sensors are attached to the lower body for data collection. The CNN [93] is used to identify the different ADL such as sitting, standing, walking, laying down, walking upstairs and walking downstairs. Furthermore, Rectified Linear Unit (ReLU) and soft-max pooling are used to improve the accuracy of the recognition. During the data acquisition, the data is collected in the form of vectors from sensors. The signals from the accelerometer and gyroscope in the inertial sensor are pre-processed and segmented in 128 different values. The performance of CNN is compared against the Multilayer Perceptron (MLP) [94] and SVM. The CNN shows better computational load and classification accuracy as compared to the other algorithms.

Key Findings:

The Deep Convolutional Neural Network (DCNN) offers the highest HAR accuracy (97.01%) as compared to SVM (96.4%) and MLP (91.7%). Similarly, the DCNN shows better performance in terms of computational load that is (3.53 seconds) as compared to SVM (10.6 seconds) and MLP (6.7 seconds). One more finding is that increasing convolution layers reduces the complexity of derived gait features that helps in distinguishing gait features accurately. However, it also increases the computational load. Finally, it is observed that wider kernel size and smaller pooling size improves the recognition accuracy of DCNN.

Limitations:

The proposed approach requires less computational power after training the data. However, the training cost of CNN is high [95].

Ordóñez and Roggen [96]:

This paper targets human activity recognition using wearables. Five different ADLs are recognized using this method. Furthermore, this study targets different sporadic right arm gestures. For data acquisition, 7 IMU sensors and 12 accelerometers are placed on the different parts of the human body. The data is pre-processed using linear interpolation [97] for channel normalization in the interval [0, 1]. The dataset is acquired after 3 hours long recording in which a subject is asked to repeat each gesture 70 times. The overall dataset is divided into classes where each class represents a feature. Furthermore, Skoda dataset [98] is used to evaluate the presented method. The DeepConvLSTM [99], consisting of 8 layers, is used for the recognition. In the proposed method, the length of the sliding window is 500 ms, and the step size is 250 seconds. The DeepConvLSTM yields

the class probability distribution for every timestamp (sliding window). Finally, the F-measure [100] (a measure of correct classification of each class) evaluates that targets the correct classification.

Key Findings:

The DeepConvLSTM offers the maximum F1-score (0.958) as compared to CNN (0.893). It is also able to distinguish closely-related activities such as opening/closing doors efficiently. One more observation is that the increasing number of layers improves accuracy but also increases the computational load.

Limitations:

The proposed study uses a Graphical Processing Unit (GPU) that consumes high energy and is thus not feasible for wearables devices. Secondly, the sample size is small (4 subjects) that is not appropriate to accumulate and analyze gait features.

Neverova [101]:

This paper's objective is the biometric authentication based on gait analysis. A time series is collected using the inertial unit of smartphone. The obfuscation based regularization is performed on the data to differentiate the notion of device and user. Furthermore, data processing is performed to generate a 14-dimensional vector consisting of normalized coordinates, magnitudes, and angles. The overall method consists of two components: feature extraction pipeline and the biometric model for the verification. A universal background model and scoring are used for continuous authentication. Dense Clock Wise Recurrent Neural Network (DCWRNN) is proposed and compared with CWRNN [102] and Recurrent Neural Network (RNN) [103] in this study. The presented DCWRNN outperforms the other algorithms in feature learning and user authentication.

Key Findings:

This paper shows that Conv-DCWRNN provides the maximum feature extraction and learning accuracy (69.41%) as compared to Conv-LSTM (68.92%) and Conv-CWRNN (68.83%). Similarly, Conv-DCWRNN outperforms the other algorithms in terms of Equal Error Rate (EER) and Half Total Error Rate (HTER). One more advantage of this scheme is that it can be used for sequential analysis of data such as gestural recognition from visual data. **Limitations:**

The performance of this scheme is highly dependent on the smartphone. The overall performance can be compromised with the orientation sensitivity and position of the motion sensor. Additionally, data collection via continuous monitoring in a dynamic environment for such long duration is challenging and thus difficult to perform/reproduce in practice?.

Zhen *et al.* [104]:

This paper aims to distinguish the ADL and fall events. A total of 500 datasets are generated for ADL and fall events via a mobile application using inertial sensors. For analysis, the threshold-based algorithm is used along with the SVM. It consists of four phases: data training, signature segment generation, feature selection, and training. The proposed model merges the angel with SVM to detect the fall. Finally,

the mobile application generates the alarm in case of a fall to notify the relented person.

Key Findings:

This paper's key finding shows that acceleration-based parameters alone achieve lower sensitivity (80%) and specificity (81.5%). In contrast, the combination of angle and acceleration parameters results in better sensitivity (99%) and specificity (96.5%).

Limitations:

The major limitation of this study is the low number of subjects (5) for analysis. Generally, a larger dataset offers better performance for feature analysis and classification.

Chen et al. [105]:

The objective of this paper is to recognize human activities for a better understanding of human behavior. The dataset provided by the Wireless Sensor Data Mining (WISDM) Lab [106] is used for the analysis. The dataset is mainly obtained using a mobile-based tri-axial accelerometer. The LSTM [107] based cell structure is used for activity recognition. The data is normalized with zero mean and standard variance for the algorithm to remove the extra noise. After that, the data is segmented using a sliding window of size 50 in the proposed model. The LSTM generates the feature vectors based on the accelerometer data that is then classified (by multi-classifier) for activity recognition.

Key Findings:

This paper shows that the LSTM-based approach for feature extraction achieves an accuracy of 92.1%.

Limitations:

The training data used in this analysis have fluctuations due to the small data-size and non-uniform distribution of data. Furthermore, the LSTM confusion matrix indicates many prediction errors in similar activities like jogging and walking upstairs. Therefore, this study requires more data, more robust regularization, or fewer model parameters.

Camps et al. [108]:

This paper targets FoG detection in Parkinson's Disease (PD) patients. During data acquisition, an IMU collects a 9-channel signal from subjects. This study uses CNN with eight layers for FoG detection. The CNN uses a window size of 2.5 seconds to achieve more accurate results. Spectral window stacking (SWS) uses the information of two consecutive 9-channel signals and joins them in the spectral domain. The SWS takes two arguments to analyze the window at a specific time t and previous time $t-1$. After that, FFT is computed for each window by keeping the first symmetric half of the window. Finally, both the windows are stacked together, resulting in a new window of 64×18 . Data augmentation transforms the training dataset in reasonably coherent identical dataset versions with a certain probability. The hyperparameter tuning process calculates such a probability to prevent overfitting. In addition, data augmentation uses shifting and rotation to distribute the same data in different parts of the sample. The first convolution layer fuses this information using a 3×18 shape kernel. The same process is followed in the first four layers with the difference in the kernel dimension. Fifth and

sixth layers are dense layers consisting of 32 neurons connected with all the input and output cells. Finally, the output layer consists of one neuron that is used for FoG detection.

Key Findings:

This study shows that the 1D-ConvNet achieves a better Geometric Mean (GM) between the sensitivity and specificity (90.6). In contrast, the most efficient state of the art algorithm based on SVM achieves a GM of 83.

Limitations:

The proposed scheme requires almost 25% more parameters for classifying one sample than SVM. It makes this scheme computationally expensive and not energy efficient for wearable sensors.

Gharani et al. [109]:

The goal of this paper is the identification of useful gait features for estimating blood alcohol content (BAC). For that, an iPhone application "DrinkTRAC" is developed to collect the gait data using the inertial sensor in mobile. DrinkTrack application asks two questions from the users regarding perceived intoxication and the number of consumed drinks. After that, the users are asked to perform a 5 step gait task via the application. Sensor fusion removes the gravitational effect to yield linear acceleration. A sliding window extracts noise free features such as mean, standard deviation, energy, and correlation in time or frequency domain. Additionally, the FFT [110] is used to compute the energy in the frequency domain. MLP, along with Bayesian Regularization Neural Network (BRNN), is used to model the relationship between the input, gait, and output (BAC value). Furthermore, it solves the overfitting problem of the data. The performance of the MLP scheme is compared with SVM and linear regression.

Key Findings:

This paper shows that the BRNN outperforms SVM and linear regression in terms of the correlation coefficient, MAE, RMSE, relative absolute error, and root relative squared error. Furthermore, the Bayesian regularization based training algorithm outperforms the Conjugate-gradient and Levenberg-Marquardt training algorithms. The Bayesian regularization shows minimum MSE of $5.09e-06$ as compared to Conjugate-gradient ($5.80e-04$) and Levenberg-Marquardt ($1.90e-05$).

Limitations:

This study uses limited ecological momentary assessment (EMA) data, almost 70%. Generally, the training with limited data can lead to the wrong interpretation of results, less accurate BAC detection in this scenario. Also, it involves only ten participants, with the majority of white females, which limits the generalizability of the solution. Therefore, this study does not apply to young adults with light alcohol use. Additionally, the difference in alcohol tolerance is not included in this study that can affect the accuracy of the solution.

McGinnis et al. [111]:

This paper aims at the gait speed measurement in patients suffering from a neurological disorder. The data is collected from two groups (sample and control group) using accelerometers. The control group consists of people with no gait impairments. At the same time, the sample has a majority

of multiple sclerosis (MS) and a few healthy persons. The subjects for both groups perform a six-minute walk test on the treadmill at three different speeds. Additionally, people with MS also conduct the Postural Control Test (PCT) [112] and complete an oral history and physical activity-related questionnaire. The accelerometer data generates the six times series from each device after applying low pass and band-pass filtering. These time series are further divided into two series with five seconds of non-overlapping windows to estimate walking speed. A total of 32 features are extracted from each window for analysis. The Support Vector Regression (SVR) [113] is used to estimate the walking speed of the subjects. The models are trained for seven combinations of sacrum using supervised machine learning. The leave-one-subject-out approach [114] is applied to improve the accuracy of the model. Furthermore, Bland-Altman limits of agreement [115] with 95% confidence interval, RMSE, and slope-intercept model is generated to analyze the performance of walking speed. Finally, the subjects are classified based on the comparison of truth values and walking speed.

Key Findings:

The paper shows that the gait speed estimation error and impairment severity are not correlated. It also shows that the data from multiple sensors and locations (sacrum, thigh, and shank) yields better RMSE (0.12 m/s) and a 95% confidence for the error of (-0.25, 0.22) m/s. In contrast, a single sensor from sacrum achieves RMSE of 0.15 m/s and error of (-0.31, 0.29) m/s. Furthermore, sensor fusion systematically overestimates speed by only 0.01 m/s.

Limitations:

The major limitation of this study is data collection from treadmill walking; therefore, it is not a generalized solution for ambulation in natural environments. Also, the model training is performed on the data of multiple groups such as control and healthy groups. A specific MS patients based model training has the potential to improve the results further.

Zhao and Zhou [116]:

This paper aims to improve gait recognition. Inertial sensors in a smartphone are used for data acquisition. Additionally, the proposed approach uses the image-based approach using the time series of inertial sensors for gait recognition. The proposed scheme consists of four steps: gait detection, angle embedded gait dynamic image (AE-GDI), feature extraction, and classifier. For gait starting position detection, a grid-based greedy method is used. Quasi-equally spaced grid is also used to overcome the peak rejection problems [117] arises by the grid-based greedy method. The AE-GDI is generated using inertial data that is composed of sliding windows. The angle generated by the data in 3D spaced is used as gait features. The AE-GDI provides the periodicity of gait features and much richer 2D features. The CNN with seven layers is used in the last two steps for the classification. Convolution layer provides a D matrix called a feature map based on the input of AE-GDI. For a richer representation of the input, each convolutional layer produces multiple feature maps. In seven layers, there are two max-pooling layers to

reduce the number of parameters and computation. Eventually, the full-length classifiers provide the required vector for the classification.

Key Findings:

The proposed scheme uses a gait segmentation algorithm based on greedy searching that results in avoiding the misjudgment of fraud/misleading gait cycles. The proposed solution shows an accuracy of 96.6% using two combined gait cycles. This accuracy is 13.6% better as compared to Cosine Similarity [118]. One more finding is that CNN, with non zero paddings in each convolution operation, offers better performance than zero paddings. The padding avoids the shrinking of data (reduction in volume size) and allows more space for the kernel to cover the data image, which helps in the more accurate analysis.

Limitations:

The AE-GDI is sensitive to sensor location and installation. The complex and noisy data from a loosely installed sensor can reduce the accuracy of the proposed scheme. Lastly, CNN is computationally expensive.

Murad and Pyun [119]:

The goal of this paper is human activity recognition using wearable sensors. Five publicly available datasets collected by wearables are used for recognition purposes [120]–[124]. These datasets consist of the activities performed in different environments. The Deep Recurrent Neural Networks (DRNN) is used for activity recognition. Data from multiple sensors is converted into windows and for the input to the DRNN model. It calculates the prediction score of each window that is fused with the softmax layer to produce the class membership probability. The DRNN model is trained using 80% of data, while the remaining 20% data is used for the testing. The mean cross-entropy [125] between the ground truth values and the predicted output is used as the cost function. It uses an optimization algorithm (Adam) [126] to reduce the cost function by back-propagating the gradient and updating the model parameters. Furthermore, the dropout techniques resolve the overfitting of data [127]. There different DRNN methods are used in this study: unidirectional DRNN, bidirectional DRNN, and cascaded DRNN. But, the accuracy of each method varies with the datasets. The proposed model is compared with various MLMs such as SVM, sequential Extreme Machine Learning (EML), CNN, and Random Forest. DRNN shows the highest classification accuracy and per-class precision.

Key Findings:

This paper shows that a four-layered unidirectional DRNN model achieves the best accuracy (96.7%) for the UCI-HAD dataset as compared to SVM (96%) and CNN (95.2%). The same DRNN model shows the maximum accuracy of 97.8% for the UCS-HAD dataset. In contrast, the three-layered bidirectional DRNN model yields the best performance for complex opportunity dataset. The cascaded DRNN model is best for the Daphnet FOG dataset and the Skoda dataset. The findings show that the introduction of sufficient deep layers helps in extracting discriminative features effectively.

Limitations:

The implementation of LSTM-based DRNN with various deep layers and hyper parameters on low power devices such as wearable sensors is a challenging task due to high computational cost.

Dehzangi et al. [128]:

This paper aims to distinguish the human based on his gait. It uses a total of 10 subjects, wearing five IMUs each, for the data acquisition. After data acquisition, the statistical approaches remove the noise from the data. Also, a 10th order Butterworth bandpass filter [129] generates the desired frequency elements from the IMUs data. Additional bandpass filtering is applied to the data for cycle extraction and interference elimination. After that, FFT transforms the signal in the frequency domain. The amplitude threshold is used to overcome the irregularities in the signal. The data cycles generated from ankle sensors are used as a reference gait cycle. After that, a time-frequency division block converts the input signal to time and frequency space. A supervised DCNN is proposed for motion-based gait authentication. It takes a 3D image as input and converts it to predictive vectors. A gradient descent method minimizes the softmax function loss during training. The overall DCNN model is composed of convolution, pooling, ReLU, and a fully connected layer. In the convolution layer, a set of predefined filters perform the convolution of the input. Pooling combines the closely associated features by applying the chosen operator. ReLU layer introduces the non-linearity in the data without changing the dimension of data. Finally, the multi-sensor fusion based on early and late fusion integrates the information from various sensors to improve the gait authentication.

Key Findings:

The analysis shows that the angular velocity shows better recognition accuracy than the acceleration data in the majority of cases. It also finds that the gyroscope is more suitable for the trunk while the accelerometer shows better results at the lower limbs. Furthermore, it is observed that the early and later fusion further increase the identification accuracy to 93.36% and 97.06%, respectively.

Limitations:

This study lacks the tuning procedure for data of different characteristics from multiples sensors and locations. Additionally, this study involves only ten participants that are not suitable for the training of the model.

Steffan et al. [130]:

The objective of the paper is to identify the stable and unstable body postures using the optimal combination of the sensors. During the data acquisition, different combinations of 6 inertial sensors are tested from 34 possible sensors placement. Also, a multi-marker motion capture system obtains the normalized motion of different subjects. The Master Motor Map (MMM) provides body data for motion analysis. Various MLMs (as defined in TABLE 8) are trained and evaluated using up to six sensors to find the optimal classification set and sensors set. Finally, the F1-score is used to determine the optimal number of sensors along with the classifier.

Key Findings:

The first key observation is that using data from more sensors do not always lead to better results. In reality, using only relevant sensors reduce the dimension of useless data and improves the outcomes. Secondly, a specific sensor location is not always optimal for every algorithm, where each algorithm offers the best performance for different places. Therefore, the best solution is based on the combination of an algorithm and sensor. A multilayer perceptron with six sensors achieves the highest F1-score of 82% as compared to SVC, Bayes, KNN.

Limitations:

This work computationally emulates the IMU data; therefore, it does not consider the noise, calibration issues, and other IMU parameters that limit the solution's generalizability.

Almaslakh [131]:

This paper targets human activity recognition with high accuracy and low computational cost. The inertial sensor (of the smartphone) collects the data from subjects while performing six different ADLs. The median filter [132] removes the noise from the data. Furthermore, the Butterworth low-pass filter [129] is applied to separate the accelerometer signals. The Stacked Auto Encoder (SAE) is applied to distinguish different ADLs. The proposed SAE consists of two autoencoders on top of each other along with a softmax layer. Overall 70% subject's data is used for training while 30% is for testing. There are two training phases: unsupervised pre-training and supervised fine-tuning. The fine-tuning of the model is done using a different number of hidden layers, the number of neurons in each layer, and the max epoch to perform the task efficiently.

Key Findings:

The SAE shows better recognition accuracy of 97.5 % as compared to multiclass linear SVM (96.4 %), AdaBoost (94.33 %) and CNN (95.75 %). Furthermore, the average recognition time of the proposed work is 0.0375 ms, which is better than the SVM time of 0.2724 ms.

Limitations:

The training of the proposed method is performed on an offline computer; therefore, it is not practical to measure and analyze gait features dynamically. Additionally, the method requires tuning the model parameters to enhance the accuracy further.

Cheng et al. [133]:

This paper aims to monitor the mobility and gait for the early detection of PD patients. The mobile-based accelerometer cumulates data from patients and control group over 24 weeks. The data is further processed with the Euclidean norm to remove 14% of passive monitoring data [134]. For activity recognition, this study uses a nine layered DNN [135]. It results in distinguishing the gait activities from stationary activities and profile the gait and balance segments with high accuracy.

Key Findings:

This study shows that passive data collection using a smartphone provides insights into daily functioning. The correlation of mobility features with the proposed system evaluates the PD severity in clinics. Additionally, the proposed model distinguishes gait activities from stationary activities with an accuracy of more than 98%.

Limitations:

The passive monitoring of data requires extensive time periods, such as 24 weeks in this case. Therefore, it is very exhaustive and time consuming for participants and well as researchers. Similarly, DNN is computationally expensive.

Zdravevski *et al.* [136]:

This paper seeks to identify the intended jogging periods automatically. Also, it investigates the system's performance using single and multiple sensors. The data is extracted from the subjects using single and multiple accelerometers. The data is segmented using two sliding windows that result in obtaining the time and frequency features. After that, the feature algorithms are applied to reduce the number of features in the dataset. Four different MLMs (SVM, Random Forest, Logistic regression, Extremely Randomized Trees) are used and compared in terms of the accuracy of correctly recognized instances.

Key Findings:

This paper shows that the identification accuracy depends on the model and feature set. For non-overlapping small segmentation window, the accelerometer placed on the hip shows better accuracy. In contrast, for large overlapping segmentation window, the ankle based accelerometer gives better performance. Nevertheless, both the approaches achieve accuracies of more than 99%. One more key finding of this paper is that the combined sensors do not provide significant improvement as compared to a single sensor. Furthermore, it finds that the logistic regression offers better performance as compared to SVM, RF and Extremely Randomized Trees (ERT).

Limitations:

The dataset is specific to fifteen years old participants. Therefore, it most likely not be able to identify jogging periods accurately in older participants.

Abdulhay *et al.* [137]:

This paper aims to diagnose PD patients using gait analysis. The gait reading is collected from patients and healthy subjects using force sensors. Eight different force sensors are placed below their shoes to measure Vertical GRF (VGRF) using a two-minute walking test. The VGRF is plotted against the time that gives various time-domain features such as the gait pattern of the subject. The time is distributed in different points to distinguish the stride phases. Furthermore, the VGRF values are passed through a Chebyshev high pass filter to remove the extra noise. The analysis shows that the gait pattern of PD patients is considerably different from normal persons. For example, the duration of stance time is longer in PD patients. Similarly, the PD patients touch the heel and toe at the same time, which is different from the

normal gait pattern. Finally, an FFT is applied to the signal in the frequency domain to classify the tremor and severity of the PD.

Key Findings:

The paper finds that a healthy person exerts more heel force on the ground as compared to toe force. In contrast, toe force is greater than the heel force for a PD person. Additionally, it shows that the relation between the frequency distribution and tremor severity. For a PD patient, the frequency peak starts shifting towards lower frequency as the disease progressed. This scheme achieves an average accuracy of 92.7 % for PD diagnose using gait analysis.

Limitations:

This paper is using general gait parameters such as stance and swing time. However, only general parameters cannot capture full information in the gait signal, which reduces the identification accuracy [138].

Gadaleta and Rossi [139]:

This paper targets authentication based on the walking style. Smartphone-based inertial sensors collect the motion data for analysis. The data is gathered over six months using five-minute sessions in variable conditions. An android application is developed to save the data from sensors and to transfer it to the cloud for further processing. After that, the cubic Spline interpolation [140] is applied to represent the data in evenly spaced points. Furthermore, a Finite Impulse Response (FIR) filter [141] helps removing motion artefacts and noise. Template-based matching is also applied to precisely assess the walking cycles regardless of the different orientation of the smartphone. In this study, CNN helps in feature extractions after the pre-processing of the data that results in the first convolution layer CL1. In CL2, the class variant and discriminant features are identified, and max-pooling is applied to reduce the dimension of the features further. Finally, the fully connected layers (FL1 and FL2) use the output of CL2 and neurons to generate the output vector that is used for authentication.

Key Findings:

This paper shows that a reliable authentication only needs fewer than five gait cycles in 80% of the cases. Furthermore, this scheme achieves a misclassification rate of less than 0.15 for gait based authentication.

Limitations:

The orientation and sensitivity of the smartphone-based inertial sensor can affect accuracy. Moreover, deep learning algorithms require high processing power.

Xia *et al.* [142]:

The topic of this paper is FoG assessment in PD patients. On-body accelerometers collect the data for analysis. Three-sigma-rule [143] helps removing the outliers, in which the mean is replaced with a median. This study uses CNN for FoG detection. For the training, the time series is divided into sliding windows of the optimal lengths. The overall detection process is divided into five portions. In the first three portions, the features are extracted using different kernel sizes and scales (with max-pooling and ReLU activation). All

the learned features in the previous layers are fused in the fourth section using two schemes. The first scheme performs the fusion by flattening and concatenating features map of each signal. The second scheme uses a convolution operator for features abstraction from the time series. Finally, section five converts the latent features in the form of vectors to distinguish different classes. Furthermore, a 10-fold classification is used on CNN that divides the data into 10 sets. One subset is used for testing, while the rest of the subsets are used for training and validation. This process is repeated ten times (using each subset for testing) to improve the detection accuracy.

Key Findings:

The study finds that there is a significant difference in normal walking and FoG gait. Also, it shows that the results from the patient dependent dataset are much better than those from the patient independent dataset. The proposed scheme using the patient dependent data set and softmax classifier achieves the sensitivity of 99.85 % and specificity of 99.99 %.

Limitations:

One drawback of this paper is the limited dataset based on ten patients. Also, some of the PD patients maintain regular gait, similar to healthy subjects. Therefore, it would be better to add more participants for data acquisition and divide them into various groups based on disease, age, etc.

Asuncion et al. [144]:

The aim of this paper is the use of gait in human authentication. Two independent inertial sensors are placed at the thighs for data acquisition using a 7 m walk. The dataset is divided into 40-48 gait cycles with roll, pitch, and yaw angles. After that, it is plotted in the form of a scalogram, as a function of time and frequency. This study uses CNN to classify each person based on the pitch, roll, and yaw. The CNN model accepts $[152 \times 300 \times 3]$ images and requires four hyperparameters and pooling layers. The pooling layer helps reducing the dimension of the data set. The "TrainNetwork" function from MATLAB is used for the data training. Additionally, stochastic gradient descent with momentum (SGDM) optimizer speeds up the training process [145]. During the cross-validation, 20% of the data is used for validation, while 80% is used for training in every kth fold. A total of four datasets are considered in which three sets are used to separately train the parameters (roll, pitch, yaw). Finally, a total of 40 (10×10) confusion matrices are generated by using left thigh yaw data that help in calculating the precision, false discovery rate (FDR), accuracy, and misclassification rate (MR) of the data.

Key Findings:

The paper shows that the combined data from pitch-roll-yaw (PRY) shows better precision and accuracy than individual parameters. The PRY data achieves 96.70 % precision and 93.02 % accuracy from the left thigh. The achieved precision is 2.88 %, and the achieved accuracy is 3.48 % higher than the best individual parameter yaw. The same trend is observed from the data of the left thigh.

Limitations:

PRY data training is more than three times longer as compared to the training time of the individual parameter. Also, the placement of the smartphone on thighs is not feasible for daily use applications.

Huang et al. [146]:

This paper targets acoustic-based gait recognition. The gait characteristics are measured using a microphone. The subjects perform a 60-70 seconds walk in the circle of seven feet diameter. The microphone detects the footstep peaks and generates a time series for analysis. The time series generates a vector consisting of mean, SD, skewness, and kurtosis. For gait recognition, multiple ML classifiers are applied, such as SVM, KNN, AdaBoost, and random forests. Finally, the less informative features are removed using feature analysis.

Key Findings:

This paper shows that each MLM offers advantages and disadvantages based on the features. For example, random forest and linear SVM offers the maximum mean score (almost 80%). Contrarily, random forest and the extra tree provides the maximum cross-validation score (0.815) using five folds. Furthermore, this study shows that the number of folds in classification algorithms can make a significant change in classification accuracy.

Limitations:

The limitation of this paper is that the acoustic-based analysis is prone to environmental noise. Minor background noise can decrease the recognition accuracy. Therefore, this solution is only applicable in controlled/laboratory environments.

Aicha et al. [147]:

This paper aims to develop an early risk detection system using wearable sensors to prevent falls. A triaxial accelerometer is used for data acquisition from a cohort aged between 65 and 99 years. Furthermore, the questionnaire and physical tests generate additional datasets. The locomotion bouts with acceleration in three dimensions are analyzed using a classification algorithm [148]. This study uses a combination of the recurrent and convolutional model called ConvLSTM for the detection. In the experiments, 90% of the data is used for training, while 10 % is used for testing. A total of five experiments are performed in this research. The first experiment compares the performance of DNN with the state of the art technologies. In the second experiment, the performance of DNN in fall prediction is measured. The third experiment explores the model improvements based on learning to identify the people depending on their gait. The fourth experiment investigates the person-specific information and its impact on model improvement. The last experiment focuses on cleaning the data to improve the overall prediction.

Key Findings:

This paper finds that deep learning models provide a higher fall risk prediction accuracy than biomechanical models. One more finding is that the ConvLSTM model is significantly faster than the LSTM model. Also, the results show that the use of general characteristics such as age and weight as auxiliary output improves the accuracy of the ConvLSTM

model. Furthermore, it is observed that the pre-processing of data improves the performance of the model.

Limitations:

The authors do not extract the gait features during the pre-processing step [149]. Furthermore, this study does not use the angle or angular velocity, which limits its accuracy.

Rescio *et al.* [150]:

This paper aims to pre-fall detection reliably and efficiently by improving the mean lead time before the impact. The data is collected using sEMGs located at the lower limbs of the subjects. For the risk assessment, the data set is generated from four different ADLs. The data is passed through the bandpass filter to remove the noise. Furthermore, the sEMG data is processed by full-wave rectification by passing through a Butterworth filter. After that, a calibration phase is performed to reduce the inter-individual variability of sEMG signals between different users. Finally, Markov Random Field (MRF) based Fisher-Markov selector and LDA are performed for features selection and classification of the pre-impact event.

Key Findings:

This paper shows that inertial based systems act slower to recognize the fall risk as compared to the sEMG-based proposed solution. Hence, the proposed solution shows the potential to detect an imminent impact due to unbalance gait faster. However, the inertial based solution provides better sensitivity and specificity (both in the range of 90-100 %) as compared to the proposed solution. The sEMG based solution achieves a specificity of 89.5 % and a sensitivity of 91.3 %.

Limitations:

This paper examines the advantages of sEMG for fall detection in a controlled environment, which limits its applicability. Furthermore, incorrect placement of sEMG probes leads to false results. Therefore, an efficient sEMG based wearable solution is required for realtime applications.

Hsieh *et al.* [151]:

This paper's aim is to identify the fall characteristics to develop a strategic plan for fall prevention. Participants perform seven different falls and six ADLs for data acquisition wearing an accelerometer. The pre-processing of data is done using a sliding window that also helps in segmenting ADL data frames. A hierarchical fall detection consisting of a threshold-based approach and a machine learning approach is used for fall detection. The threshold-based approach aims to identify falls and ADLs. The SVM is used in a machine learning approach to train fall events classifiers using a kernel-based on radial basis function (RBF) [152]. Finally, the fall direction identification is used on the identified fall events.

Key Findings:

The proposed scheme achieves high sensitivity (99.83 %), specificity (98.44 %), precision (98.67 %), negative predictive value (98.44 %), and accuracy (99.19 %) for fall detection. The same trend is also visible in fall direction identification. It shows that the highest fall direction identification error is in the backward and left lateral direction, and the lowest error is in the forward direction.

Limitations:

This study is unable to distinguish the fall and lying activity efficiently. Therefore, it generates a high percentage of false-positive results (16.67%) for lying activity.

Putra *et al.* [153]:

This paper aims to align the falls with the characteristic features of the fall stages for the better identification of falls. Additionally, this paper addresses the multi-peak problem using event-triggered machine learning approach EvenT-ML. The EvenT-ML approach consists of the initial buffer, peak detection, sample gathering, and multi-peak detection. The data is acquired using an accelerometer from the subjects while doing falls and various ADLs. Additionally, a second dataset is obtained from young adults in which each person performs several falls and ADLs. Finally, different classifiers such as CART, k-NN, LR, and SVM are used for training and testing, while the F-score is used to analyze the algorithm's performance.

Key Findings:

The paper shows that features such as acceleration exponential moving average, velocity, and energy expenditure after aligning with fall stages improve the fall detection rate and computational cost. Additionally, the proposed EvenT-ML achieves better precision, recall, and F-score value as compared to the fixed-size non-overlapping sliding window (FNSW) and fixed-size overlapping sliding window (FOSW) approaches. Also, the LR combined with EvenT-ML achieves the best results as compared to KART, KNN, and SVM.

Limitations:

The study uses a binary classification for fall activities that results in identifying the near-fall event as a fall event, which decreases fall detection accuracy.

Ghazali *et al.* [154]:

The goal of this paper is to identify various sports activities using IMU. For data collection, the participants are asked to perform walking, running, jumping, and sprinting. The data is pre-processed and labeled based on activities with a sliding window of 2.56 seconds. Finally, a total of 24 features are extracted based on accelerometer data. Finally, different classifiers such as DTs, SVM, discriminant analysis, KNN, and ensemble classifiers are used and compared in terms of correctly identifying the sports activities.

Key Findings:

This paper shows that the cubic SVM achieves the highest accuracy (91.2 %) for sports activity recognition as compared to DT, DA, KNN, where this accuracy is less than 90 %.

Limitations:

The major limitation of this study is the confusion between the jogging and sprinting activities, reflected by a high percentage (20%) of false-negative results for sprinting activity.

Rastegari *et al.* [155]:

This paper aims at finding the optimal gait features to improve the assessment and diagnosis of gait. For analysis, the data is collected using accelerometers from the healthy elderly, mild PD patients, and geriatrics. The subjects perform a 10 meters normal walk without any hindrance four times.

The data represents the stride level features as well as the overall gait sequence. Statistical approaches have been used to remove the noise from the data. The maximum information gain minimum correlation (MIGMC) approach is used to achieve the appropriate gait features. Also, pair-wise Pearson correlation analysis identifies the highly correlated features [156]. For the features selection, ANOVA and Tukey posthoc comparison tests are used [157], [158]. Finally, different MLMs (SVM, Random Forest, Bagging, and AdaBoost) are compared using 5-fold cross-validation.

Key Findings:

This paper emphasizes selecting the optimal gait features to reduce the data dimension and computational cost. It shows that AdaBoost provides the best classification accuracy (100 %) among all the available models based on standardized feature vectors, whereas Bagging offers the second-best accuracy of 96.7 %. In contrast, SVM achieves the best performance for non-standardized feature vectors.

Limitations:

A small scale dataset is used in this study, which is prone to overfitting during training. Additionally, other efficient feature selection schemes are not compared with MIGMC.

Gurchiek et al. [159]:

The goal of this paper is to detect asymmetric gait patterns in patients recovering from anterior cruciate ligament reconstruction [160]. The data is collected from the patients using the three axis-accelerometer and surface EMG. The overall analysis consists of three steps: stride segmentation, stride biomechanical analysis, and walking identification. For walking identification, the accelerometer data is divided into four windows to extract 11 time and frequency features. These features act as an input to SVM to identify walking spell. For training, the data is collected from healthy subjects to distinguish the walking pattern of patients. Welch's method [161] is used to estimate the power spectral density for stride segmentation. For biomechanical analysis, the principal component of acceleration time-series is used. The SEMG data and acceleration data is resampled as stride percentage and categorized into two groups. The statistical analysis of both groups is capable of detecting gait asymmetries for early post-surgery.

Key Findings:

This paper observes that the symmetry between the affected and unaffected legs is significantly less during slow walking for early post-surgery group T1 (range: 1.1 – 5.3 weeks) than later group T2 (range: 14.3 – 19.1 weeks). In contrast, fast walking shows no significant difference in gait symmetry of both groups.

Limitations:

The incorrect placement of sEMG probes leads to false results and affect the accuracy of the scheme. Additionally, this study includes a limited dataset based on only eight patients.

Zhang et al. [162]:

This paper aims to improve the accuracy of gait analysis using wearables. SportSole consisting of two insole modules

and a data logger collects the data. Each module comprises an IMU, a logic unit, and a piezo-resistive sensor. This study includes only healthy subjects who perform a 10-minute warm-up. After that, the persons walk/run on a treadmill with variable speed to measure the average preferred speed. Then the subjects perform two sessions consisting of running and walking. After each session, the insole module is detached to record the data. The optical motion capture system combines with force plates to provide the ground truth values. For example, the force plates calculate the stride length of each person. Similarly, piezo-resistive sensors measure the timing of heel strike and toe-off. Multivariate linear regression with the least absolute shrinkage and selection operator (LASSO) helps avoid the overfitting of data [163]. The SVR is applied to estimate the gait specific parameters. For data training, subject-specific and generic training methods are used. In the subject-specific model, SVR and LASSO models are trained independently for each subject. Contrarily, in the generic model, both the models are trained subject by subject, using the data from all the subjects. Additionally, intraclass correlation coefficients (ICC) [164] is used to measure the reliability of the test.

Key Findings:

This paper shows that the subject-specific method offers higher accuracy and reliability than the generic methods. Additionally, the SVR outperforms the LASSO models in terms of accuracy and validity, especially while using generic models.

Limitations:

This study includes only fourteen young adults (age 23.1 ± 4.0 years), and their features are extracted using a treadmill. Hence, it limits the generalizability of the system. For the real-life applicability of this solution, it is essential to include more participants from different age ranges, and analysis should be done in a dynamic environment/ground.

Abujrida et al. [165]:

The paper's aim is to distinguish the PD patients and the severity of the disease based on the gait. A smart-phone's sensors (accelerometer and gyroscope) collects the data from different sets of patients. Participants stand and walk for thirty seconds each, and accelerometer data is sampled at 100 Hz. Additionally, surveys filled out by the patients gather additional lifestyle data. The data signals are divided into five seconds intervals, and averaging helps smoothing the results. The peaks in the signals estimate the walking segment steps. After pre-processing, the gait features are extracted from the gathered data. Furthermore, the time features are calculated directly while frequency features are calculated using FFT and power spectral density (PSD) [166]. A supervised classification using 10-fold cross-validation measures the precision and accuracy of the data. For assessment, multiple ML classifiers are applied, such as Binary Tree, weighted KNN, logistic regression, fine tree, quadratic discriminant, random forest, and cubic SVM.

Key Findings:

The paper shows that random forest provides the best accuracy of 93% in the classification of PD patients and detecting walking balance severity. In contrast, Bagged trees give the maximum accuracy in identifying FoG (98%) and shaking tremor severity (95%). Furthermore, it is observed that lifestyle features improve classification results.

Limitations:

The introduction and analysis of various signal segmentation strategies, such as bayesian segmentation, can improve the proposed solution's performance.

Kim et al. [167]:

This paper deals with FoG assessment in PD patients. During this study, inertial sensors in the smartphone acquire the data from samples. Videos are also recorded using a smartphone for FoG assessment and posterior referral review. Moreover, two more smartphones compare detection performance. A mobile application using socket communication is developed to synchronize the timing of all the smartphones. The subjects perform three meters walk tests. Furthermore, to provoke FoG, subjects also perform other activities such as opening a door, and turning around and entering it. The data is sliced in 2.5 seconds and converted into the frequency domain using FFT. The CNN consisting of 2 layers and 20 filters, is used for FoG detection. 10-folded cross-validation is performed in which 90% of the data is used for the training. The first layer uses a convolution filter of 1×50 size. The max-pooling layer after the convolutional layer achieves spatial invariance. A kernel of 6×25 fuses the data from various sensors. ReLU, in all the convolution layers, removes the negative outputs. The Softmax classifier in the final layer classifies the final output. Finally, the performance of CNN is compared with random forest, MLP, DT, SVM, and NB.

Key Findings:

This paper shoes that CNN outperforms the rest of the algorithms in terms of F1-score (91.8%), sensitivity (93.8%), and specificity (90.1%) in detecting FoG. The second best algorithm (random forest) provides a F1-score of 73.5%, sensitivity of 70.8%, and specificity of 89.1%. The second key finding is that the sensor placement the waist as a reference provides the highest precision and specificity compared to the placement in a pocket or at the ankle.

Limitations:

The computation cost of the proposed solution for testing and detection is too high for a smartphone and therefore requires the use a remote server for data processing.

Wang et al. [168]:

This paper aims to reduce the knee adduction movement (KAM) using wearables. This study uses two IMUs for data acquisition from the subjects with Body Mass Index (BMI) less than 35. The IMU sensors transmit the data directly to the mobile application that is then sent to the cloud for processing. Furthermore, the low pass filter and Butterworth filter refine the IMU signals. The IMU built-in model is used to compensate for the zero drift error. Moreover, a real-time segmentation algorithm helps removing the extra noise in the

data. The ANN and XGBoost algorithms are implemented to estimate the KAM. Both the algorithms are compared with the measurements from a laboratory setup. The proposed ANN uses ten layers with 256 neurons in the first six layers, 128 neurons in the 7th and 8th layers, and 64 neurons in the last two layers. The RMS optimizer is used for data training with a learning rate of 0.001 [169]. In this study, 80% of the data is used for training, while 10% data is responsible for validation and 10% for testing.

Key Findings:

This paper shows that the ANN is slightly more accurate in KAM estimation than the XGBoost model. The ANN shows a regression fitness values of 0.956 as compared to the 0.947 of XGBoost. The second key finding of this paper is that the sensors' stability is affected by its battery level.

Limitations:

Issues related to chosen data communication architecture: the gait training system of the proposed approach is based on the Message Queuing Telemetry Transport (MQTT) server. The MQTT server always requires a stable and robust internet connection to provide real-time feedback. Additionally, it only incorporates the foot progression angle for KAM estimation that limits its efficiency. The combination of other gait parameters, such as trunk leaning and knee thrust gait, can improve the performance of the system.

These papers are further analyzed based on various parameters such as the distribution by years, venue type, applications, and suitable algorithm for the desired application. A qualitative synthesis of the selected papers is given in Section V-B.

B. QUALITATIVE SYNTHESIS

A qualitative synthesis of the selected papers is presented in this section.

1) YEARLY DISTRIBUTION

We aim to highlight the latest trends in the domain of gait analysis. Therefore, we have only considered the papers from 2015 onward. The key search of gait analysis on google scholar shows 167,00 entries. It highlights that a lot of researchers are showing interest in this domain. However, we are specifically interested to study the interplay of ML, gait analysis and the role of wearable devices. Our initial findings show a total of 754 papers based on the title, as shown in Section II. However, the papers meeting our criteria are only 33, which is only 4.37% of pre-screening results. Therefore, the gait analysis using ML and wearable sensors require further attention of the researchers. The primary reason for such a solution is its applicability in an inclusive environment. Furthermore, MLs prove to be more accurate for gait-based applications, especially in classification and identification applications. The yearly distribution of the publications is presented in Figure 5. There are a total of 33 selected studies in this domain, with an average of 5.5 papers per year. The figure shows that the highest percentage of selected papers belongs to the years 2017 and 2018, i.e., approximately 60%.

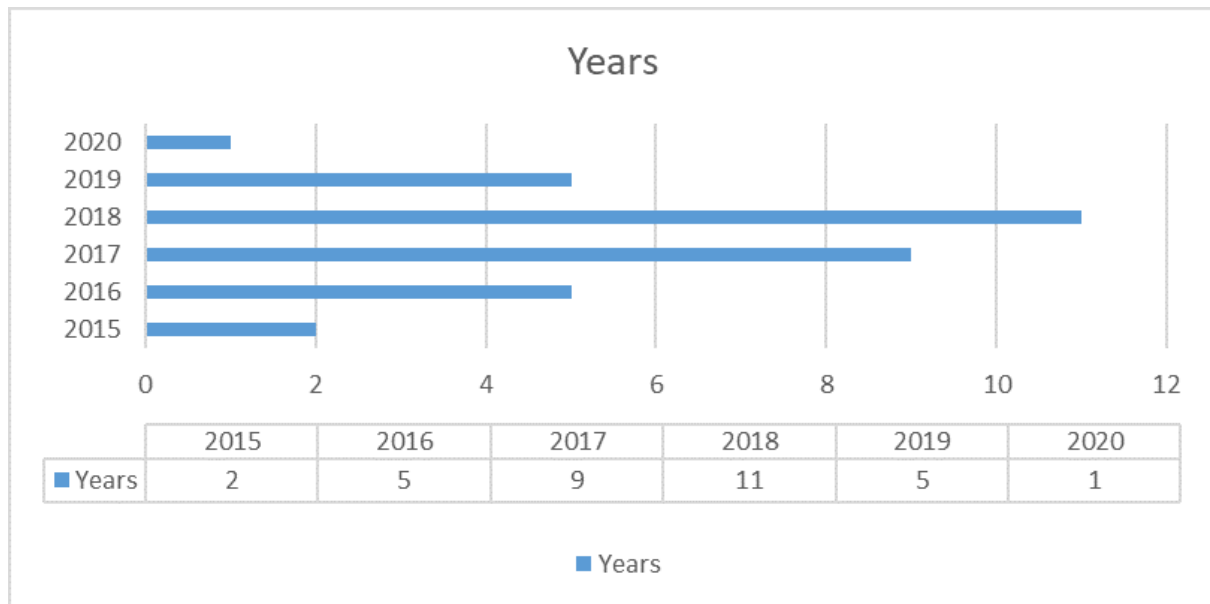


FIGURE 5. Yearly distribution of selected papers.

The year 2019 show a relatively lower interest in wearable sensors with ML as compared to 2017 and 2018, yet it is comparable to 2016. At the time of writing (May 2020), it is not possible to comment on 2020 since the actual number of related publications can only be confirmed once the year is over.

2) PUBLICATION TYPE DISTRIBUTION

We have only selected conference and journal papers for this review. Therefore, other publications such as posters, abstracts, and patents have been removed during the screening process. The distribution percentage based on the conference/journal format is presented as a pie chart in Figure 6. The figure shows that most of the selected papers belong to the journal category (63.64%).

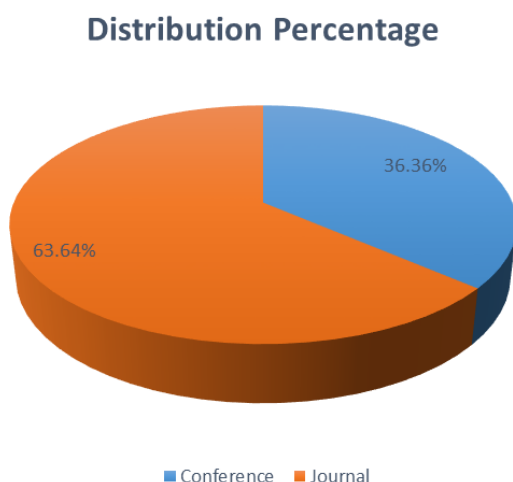


FIGURE 6. Publication distribution in conference and journal.

3) VENUE DISTRIBUTION

This section presents the distribution of selected papers in terms of publication venue in Figure 7. The studies are published in IEEE, Elsevier, MDPI, Hindawi, PLOS One, and other venues such as Taylor & Francis and Mary Ann Liebert. From the figure, it is clear that most of the publications belong to IEEE (37%) and MDPI (21%). Therefore, these two venues are suitable for the publication of gait analysis, wearable sensors, and applications. The most frequent venue in our analysis is MDPI's sensor journal with six studies. Therefore, it is recommended to consider this journal to submit such manuscripts.

4) DISTRIBUTION BASED ON ML

One of main aims of the paper is to review, structure and classify research studies involving gait analysis driven by MLs. Therefore, it is vital to highlight the most frequently used MLs. The percentage distribution of selected learning algorithms is presented in Figure 8. From the figure, it is clear that most of the papers are using SVM or CNN. The main advantage of SVM is that it works well with unstructured data [155]. It also works well in the presence of a small dataset. The majority of studies in our analysis lack a significant amount of participants. Hence, such studies use SVM due to its ability to work well in the presence of a small sample size [151], [159]. Lastly, the SVM is computationally less expensive and generates faster results as compared to deep learning approaches. Because of that, it is frequently used in fall detection and prevention systems. In contrast, CNN is computationally expensive but generates more accurate results. So, it is often used in intricate and closely related gait patterns where accuracy is essential such as authentication

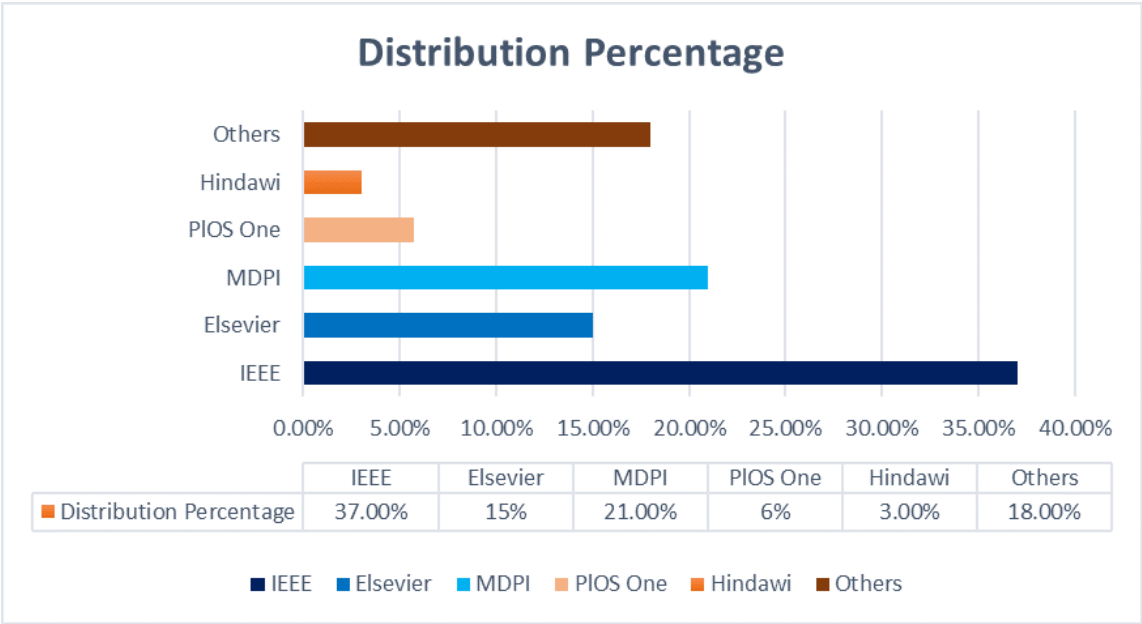


FIGURE 7. Publication distribution based on venue.

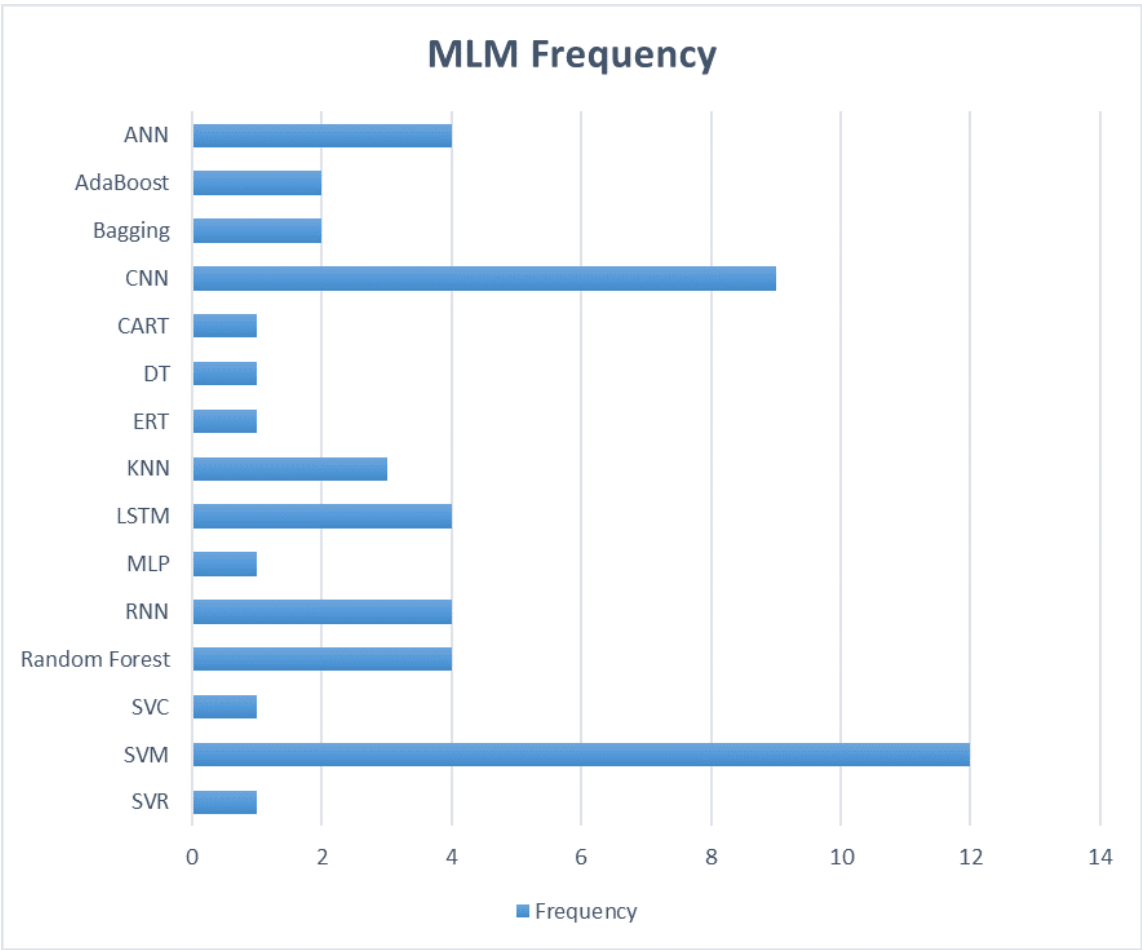


FIGURE 8. Frequency of MLMs in selected papers.

and HAR. However, there is also a good interest in RNN, Random forest, LDA, and LSTM.

5) APPLICATION SCENARIOS

Gait analysis provides applications in the domain of health, fitness, and security. The applicability of selected papers is highlighted in TABLE 5.

TABLE 5. Application domain of selected papers.

Paper	Medical	Fitness	Security
Wu et al. [86]	✓	✓	
Chen et al. [89]	✓	✓	
Zebin et al. [92]	✓	✓	
Ordóñez et al. [96]			✓
Neverova et al. [101]			✓
Zhen et al. [104]	✓	✓	
Chen et al. [105]	✓	✓	
Camps et al. [108]	✓		
Gharani et al. [109]	✓		
McGinnis et al. [111]	✓		
Zhao et al. [116]	✓	✓	✓
Murad et al. [119]	✓	✓	
Dehzangi et al. [128]			✓
Steffan et al. [130]	✓	✓	
Almaslukh et al. [131]	✓	✓	
Cheng et al. [133]	✓		
Zdravevski et al. [136]		✓	
Abdulhay et al. [137]	✓		
Gadaleta et al. [139]			✓
Xia et al. [142]	✓		
Asuncion et al. [144]			✓
Huang et al. [146]	✓		✓
Aicha et al. [147]	✓	✓	
Rescio et al. [150]	✓	✓	
Hsieh et al. [151]	✓	✓	
Putra et al. [153]	✓	✓	
Ghazali et al. [154]		✓	
Rastegari et al. [155]	✓		
Gurchiek et al. [159]	✓	✓	
Zhang et al. [162]	✓	✓	
Abujrida et al. [165]	✓		
Kim et al. [167]	✓		
Wang et al. [168]	✓	✓	

As mentioned in Section III, these applications are subdivided into specific groups such as HAR, disease diagnosis, gait classification, and injury avoidance. TABLE 6 lists the publications according to their applicability and percentage of papers. The Table shows that roughly 50% of the works are related to authentication, HAR, and disease diagnosis. Additionally, TABLE 7 presents the applications with the widely used MLMs, types of wearable sensors, and their placements, based on a careful analysis of the papers.

6) SAMPLE SIZE DISTRIBUTION

MLMs require a dataset for training. For that, each study used different data based on the application; for example, the disease identification dataset generally involves two groups: patient group and control group. The overall distribution of the number of participants in each study is illustrated in Figure 9. Thirty-four percent of studies use a maximum of ten participants for the training and testing of their solution. Similarly, 25% of the publications include participants in the

TABLE 6. Classification of papers based on potential applications.

Application	Papers	Percentage
Authentication	[139], [144], [146], [96], [116], [128], [101]	15 %
BAC Estimation	[109]	2%
Disease Diagnosis	[137], [155], [159], [165], [111], [146], [86], [133]	18%
Fall Detection	[104], [153]	5%
Fall Prevention	[147], [150], [151], [130]	9%
Fitness Monitoring	[162], [136]	5%
FoG Detection	[142], [108], [167]	7%
Gait Classification	[162], [116]	5%
Gait Improvement	[86], [168], [136]	7%
HAR	[92], [96], [119], [150], [131], [89], [105], [133]	18%
Injury Avoidance	[159], [162]	5%
Rehabilitation	[168]	2%
Sports Biomechanics	[154]	2%

TABLE 7. Most frequently used parameters for a specific application.

Application	MLM	Wearable Sensor	Placement
Authentication	CNN	IMU	Hand, Pocket (mobile)
BAC Estimation	ANN	IMU	Pocket (mobile)
Disease Diagnosis	SVM	Accelerometer	Thigh, Shank
Fall Detection	SVM	Accelerometer	Waist
Fall Prevention	SVC & SVM	Accelerometer	Waist
Fitness Monitoring	SVM & SVR	IMU	Foot
FoG Detection	CNN	IMU	Waist, Thigh
Gait Classification	CNN & SVR	IMU	Pocket, Foot
Gait Improvement	SVM	Accelerometer	Trunk, Hip, Knee
HAR	LSTM & CNN	IMU	Waist, Arms, Thigh
Injury Avoidance	SVM & SVR	IMU	Leg, Feet
Rehabilitation	ANN	IMU	Ankle
Sports Biomechanics	SVM	IMU	Chest

range of 11-30. Generally, large datasets improve decision-making accuracy. However, the analysis shows that most of the studies fail to accumulate enough participants. Therefore, the datasets used in these studies are not optimal, as already pointed out in some studies.

Figure 10 further highlights the sample size against the designed application. For example, authentication studies generally require smaller data sets for the training. In 57% of the authentication studies, the dataset consists of ten or less than ten samples. Similarly, fall detection applications are also designed using less than 50 sample size. In contrast, the gait improvement studies often use a sample size of 51-100. This figure presents a generic overview of the sample size distribution for each application. However, we cannot conclude that such data sizes are optimal for each application.

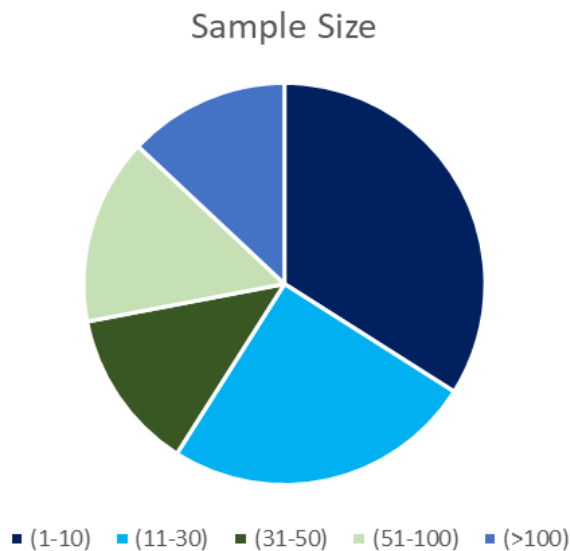


FIGURE 9. Sample size distribution.

The reason is a limited number of studies in our review and fewer participants for the dataset in most of the studies.

Furthermore, we aim to highlight the latest research trends in wearable and ML that narrow down the selection of papers. An overview of critical parameters of studies such as sampling rate, wearable sensors, number of sensors, performance parameters, and simulation tool is given in TABLE 8.

VI. FUTURE DIRECTIONS

This section presents the open research challenges and possible future direction in the domain of gait analysis.

A. SECURITY

Gait based authentication is attracting various researchers [96], [144], [146]. Having said that, it is still relatively less explored domain, as illustrated in TABLE 5. Gait analysis can further improve the security and authentication using the fusion of gait and other biometrics such as voice, retina, and face. In this context, the authors in [170] improves the authentication rate by combining the gait and face biometrics. However, this is just an initial attempt in this domain. Further analysis of other single and multiple biometrics with gait is an exciting future challenge. Besides authentication, the design of a secure mechanism for gait analysis is also required to prevent external attacks such as spoofing [171].

B. SENSOR FUSION

Sensor fusion aims to combine the data from multiple sources into one data. The resulting dataset is more accurate as it merges the features of numerous sources [172], [173]. Sensor fusion is further divided into homogeneous fusion and heterogeneous fusion. Homogeneous sensor fusion uses the same type of sensors (wearable-wearable). In contrast, heterogeneous sensor fusion merges data from different types of sensors (wearable-vision) [174], [175]. Both fusion approaches

can improve the effectiveness of the data leading to better decision accuracy. Therefore, sensor fusion would be efficient in the development of gait based applications.

C. COVARIATES

The latest vision-based schemes have significantly improved the efficiency of gait recognition. However, the accuracy of the recognition based algorithm starts decreasing in the presence of external covariates such as clothes, shoes, and bags [176]. Therefore, the design of the covariate aware scheme to improve gait recognition is an exciting research topic. For example, a random subspace method is presented in [177] for clothing-invariant gait recognition. However, the maximum achieved accuracy in the presented study is 80%. More efficient methodologies are required to resolve the covariate issue with high efficiency.

D. OPTIMAL POSITION OF WEARABLE SENSORS

Gait analysis provides information about human locomotion employed in various domains such as health, fitness, and security. It aims to maximize the interpretable information using wearable sensors. However, multiple factors such as the movement of cloths, vibration, and placement of sensors in pocket induce interference leading to degrading the quality of data [178], [179]. Therefore, it is mandatory to investigate the sensor's optimal location to improve the quality of the acquired data. In this context, the authors in [180] find the optimal foot location for the IMU placement to enhance the quality of the data. However, the location of wearable varies to the application requirements. Therefore, further research is needed for optimal placement of wearables for applications such as fall detection, fall prevention, and fitness monitoring.

E. ENERGY EFFICIENCY

The significant advantage of the wearable sensor is the ability to provide continual monitoring. However, the constant tracking, computing, and, especially continuous (wireless) data transfer, result in depletion of light-weight device batteries. It can affect the overall Quality of Life (QoL) in critical scenarios. Therefore, the design of energy-efficient ML frameworks for microcontrollers and energy efficient raw data processing is an excellent future direction. For example, an adaptive framework based on selective sensing is presented in [181] to improve the system's energy efficiency. However, the given scheme reduces the number of samples that can affect the accuracy of the application. Therefore, more energy and performance efficient algorithms should be designed to address this problem, especially on sensing devices. Additionally, the use of energy harvester is a promising solution to resolve energy crises in wearable sensors [182]–[184].

F. CONTEXT AWARENESS

Different locomotion parameters such as stride length, stance time, and velocity are examined during gait analysis. However, the condition of the walking surface significantly affects

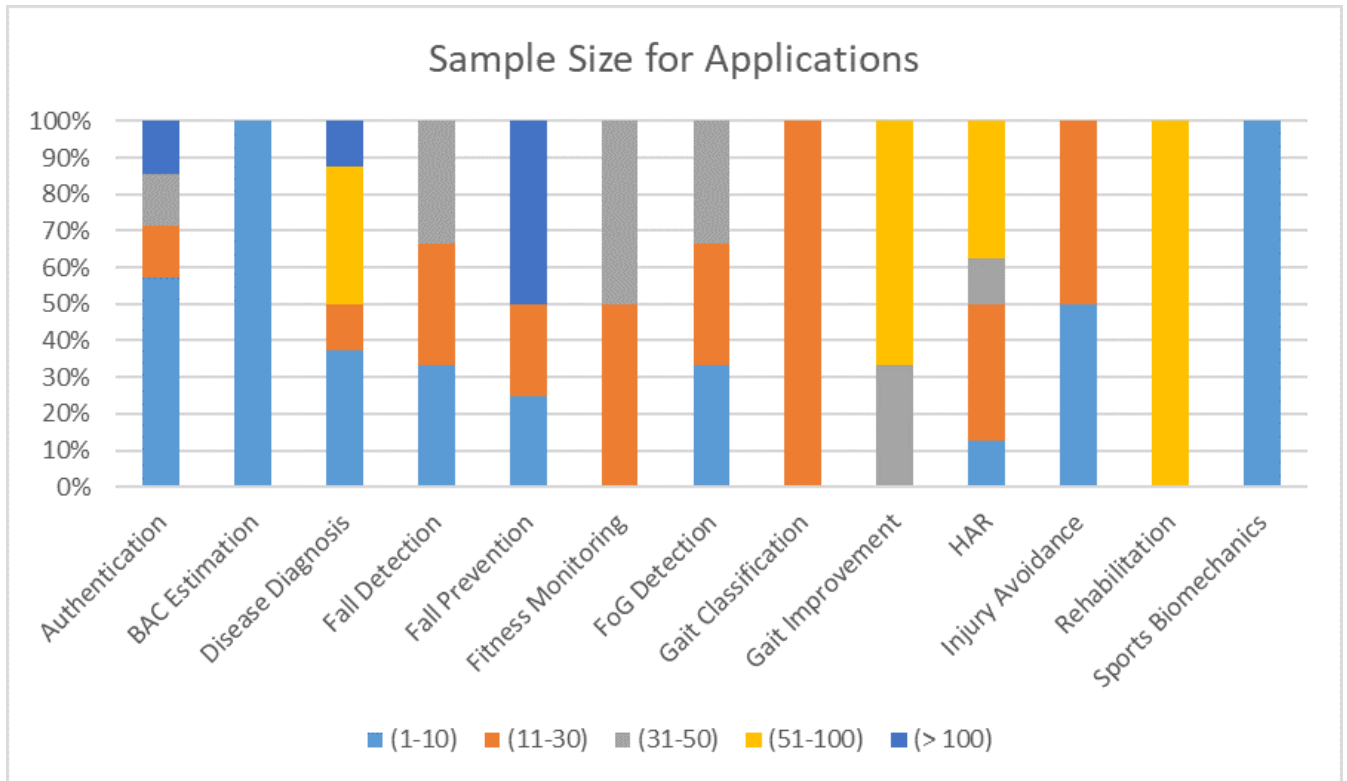


FIGURE 10. Sample size distribution for applications.

the gait parameters [185]. For example, the uneven surface reduces the velocity and step length of the older population [186], [187]. Therefore, context awareness is an essential requirement for the applicability of gait analysis in the outdoor environment. In this context, the authors of [188] show the awareness of the slippery surface leading to a cautious gait and resulting in fewer falls. However, further research is required to analyze the locomotion pattern on various surfaces such as steep surface, sandy surface, and uneven surface.

VII. OVERVIEW OF KEY PARAMETERS

A. WEARABLE DESIGN

Wearable sensors aim to measure gait parameters in outdoor as well as indoor places. Generally, these sensors are worn for a more extended duration of time. In some cases, the prototype consists of multiple units, such as sensors, electrodes, and controllers. Therefore, such solutions are not optimal for a user's perspective. Ideally, a wearable needs to provide comfort to the user [189], [190]. This aspect is often neglected during prototype development. Therefore, one future challenge is to work on a wearable designs that are comfortable and aesthetically pleasing. For example, [191] targets the design of the wearable system based on closed-loop control of the gait restoration system by functional electrical stimulation. But, this design is specific to the sensor's placement at a single leg. The analysis shows that various other locations

such as waist and lower back results in better accuracy for a few applications. Hence, the comfortable and usable design of such prototypes that requires multiple sensors placements is an interesting future challenge.

B. PREPARATION OF DATASETS

The gait analysis mainly depends on the kinematics data. Each dataset differs based on feature extraction and locomotion pattern. The large datasets result in improving the accuracy of gait analysis. One major limitation of most studies, as mentioned earlier, is the limited dataset. Therefore, the preparation of large public datasets using different walking patterns is a possible future direction. Additionally, the researchers can compare or fuse the results of these datasets with their datasets to improve the performance of their study. The use of Generative Adversarial Network (GAN) is also an interesting methodology to improve the dataset when real data is not enough [192].

C. LIGHTWEIGHT ALGORITHMS

Generally, the wearable sensors offer limited computing, memory, and energy resources that cannot be easily increased [193]. The use of the cloud for processing the wearable data is one solution [194]. However, it adds extra latency that is not optimal for the design of critical applications such as fall prevention. Therefore, the design of a lightweight processing and classification algorithm is an important future challenge.

TABLE 8. Overview of key parameters.

Ref.	Year	MLM	Wearable Sensor	No of Sensor	Sample Size	Sensor Placement	Sampling Rate	Performance Parameter	Tool
[86]	2015	SVM	Force Sensor	1	60	Below Foot	400Hz	Acc: 90%, Sen: 90%, Sep: 88%	N/A
[89]	2015	CNN	Accelerometer	1	100	Pocket, Waist	100Hz	Acc: 93.8%	Mobile Application
[92]	2016	SVM, MLP, CNN	IMU	5	12	Pelvis, Thighs, Shanks	N/A	Acc: 97.01%	MATLAB
[96]	2016	DeepConvLSTM	IMU, Accelerometer	7, 12	4	Back, Hip, Feet, Arms	30Hz	Acc: 95.8%	N/A
[101]	2016	Conv-RNN, Conv-CWRNN, Conv-DCWRNN	IMU	1	1500	Hand	200Hz	Acc: 94.02%, EER: 18.17%	Theano
[104]	2016	SVM	IMU	1	5	Waist	100Hz	Sen: 99%, Sep: 96.5%	Ecllips
[105]	2016	LSTM	Accelerometer	1	N/A	NA	N/A	Acc: 92.1%	Mobile Application
[109]	2017	ANN, BRNN	IMU	1	10	Pocket	100Hz	RMSE: 0.0226, MAE: 0.0174	DrinkTRAC Application
[111]	2017	SVR	Accelerometer	5	10	Sacrum, Thighs, Shanks	50Hz	RMSE: 0.14	Scikit-Learn
[116]	2017	CNN	IMU	1	20	Pocket	50Hz	Acc: 96.6%	TensorFlow
[119]	2017	LSTM based DRNN	IMU, Accelerometer	Variable for datasets	21	Variable for datasets	30-100Hz	Acc: 94.1%	TensorFlow
[128]	2017	DCNN	IMU	5	59	Chest, Lower-back, Right Wrist, Right Knee, Right Ankle	50Hz	Acc: 97.01%	MATLAB

Continued on next page

TABLE 8. (Continued.) Overview of key parameters.

Ref.	Year	SVC, Bayes, ML perceptron	MLM	Wearable Sensor	No of Sensor	Sample Size	Sensor Placement	Sampling Rate	Performance Parameter	Tool
[130]	2017	SVC, Bayes, ML perceptron		IMU	6	154	Feet, Head, Shoulders, Hands, Arms, Waist	100Hz	F1-score: 82%	SciKit-learn, Simox Toolbox
[131]	2017	SAE		IMU	1	30	Waist	50Hz	Acc: 97.5%	MATLAB
[133]	2017	DNN		Accelerometer	1	79	N/A	20Hz	Acc: 96.9-99.5%	N/A
[136]	2017	SVM, Random Forest, LR, ERT		Accelerometer	1	39	Hip, Knee	30Hz	Acc: 99%	SciKit-learn
[108]	2018	CNN		IMU	1	21	Waist	50Hz	Acc: 90.6%	N/A
[137]	2018	SVM		Force Sensors	8	93	Below Feet	100Hz	Acc: 92.7%	MATLAB
[139]	2018	CNN, SVM		IMU	1	50	Pocket	100-200Hz	FPN < 0.15%	MATLAB
[142]	2018	CNN		IMU	3	10	Lower Back, Thigh, Shank	64Hz	Acc: 90.6%	MatConvNet Toolbox
[144]	2018	CNN		IMU	2	10	Thighs	N/A	Acc: 98.34%	MATLAB
[146]	2018	KNN, SVM, Random Forest, AdaBoost		Microphone	1	10	N/A	44.1KHz	Acc: 81.5%	Windows Sound Recorder
[147]	2018	ConvLSTM		Accelerometer	1	296	Lower Back	100Hz	Acc: 95%	DAS-5 Server
[150]	2018	Custom MLM based on LDA and Fisher-Markov selector		sEMG	4	15	Gastrocnemius, Tibialis Muscles	512Hz	Sen: 91.3%, Sep: 89.5%	MATLAB, EMG Analyzer
[151]	2018	SVM		Accelerometer	1	8	Waist	128Hz	Acc: 97.34%, Sen: 98.52%, Pre: 97.49%	N/A

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TABLE 8. (Continued.) Overview of key parameters.

Ref.	Year	MLM	Wearable Sensor	No of Sensor	Sample Size	Sensor Placement	Sampling Rate	Performance Parameter	Tool
[153]	2018	EvenT-ML, CART, k-NN, LR, SVM	Accelerometer	1	46,21	Chest, Thigh, Waist	100Hz	F-score: %	LabVIEW, Scikit-learn
[154]	2018	DT, SVM, DA, KNN, Ensemble Classifiers	IMU	1	10	Chest	N/A	Acc: 91.2%	MATLAB
[155]	2019	SVM, Random Forest, AdaBoost, Bagging, Naïve Bayes	Accelerometer	2	30	Ankles	102.4Hz	Acc: 96.7%	WEKA
[159]	2019	SVM	Accelerometer, sEMG	1, 1	8	Leg, Rectus Femoris	30Hz	Acc: 92%	MATLAB
[162]	2019	SVR	IMU	2	14	Feet	300-900Hz	MAE: 1.2%	MATLAB
[165]	2019	Random Forest, Bagged Trees	Accelerometer, Gyroscope	1	456	Pocket	100Hz	Acc: 98%	MATLAB
[167]	2019	CNN	Accelerometer, Gyroscope	1	32	Pocket	50-200Hz	Acc: 91.8%	TensorFlow
[168]	2020	ANN	IMU	2	90	Bilateral Malleoli (Ankle)	100Hz	RMSE: 0.004	Mobile Application

In this context, a lightweight deep learning model is presented for HAR in [195]. However, further work is required for time-critical applications such as fall prevention.

D. WEARABLE DEVICES CONNECTIVITY

Institute of Electrical and Electronics Engineers (IEEE) and European Telecommunications Standards Institute (ETSI) have presented communication standards for vital monitoring using sensors. A few notable standards are IEEE 802.15.6 Wireless Body Area Network (WBAN) and ETSI smartBAN [196]–[198]. These standards support lightweight sensors to improve the Quality of Service (QoS) connectivity parameters such as energy efficiency and throughput [199], [200]. However, to the best of our knowledge, there is no existing such standards compatible device. Therefore, one important future research direction is to design and develop these standard compatible devices to improve the performance of remote gait analysis. Furthermore, there are other limitations of BANs such as interference, security, error correction, and re-transmission strategies requiring attention in the future.

E. SMARTPHONE APPLICATIONS AND USER INTERFACE (UI)

With the increase in the use and processing power of the smartphone, a mobile-based gait analysis is performed in most of the studies [201], [202]. Therefore, the development of smartphone applications for gait measurements is a possible future direction. Having said that, most of the users are old and less technology aware. Furthermore, doctors are also using such mobile devices for remote health monitoring. Therefore, the design of the application user interfaces with excellent usability and visibility is also an exciting future aspect.

VIII. CONCLUSION

Gait analysis facilitates the design of various applications in the domain of healthcare, security, sports, and fitness. Wearable sensors are widely used to collect gait parameters because of their size, price, and ability to operate in the external environment. This paper explores the latest trends in gait analysis using wearable sensors and MLs. At first, an overview of gait analysis and wearable sensors is presented. It discusses crucial gait parameters, wearables, and their applicability in gait analysis. Secondly, a detailed analysis of the recent studies is performed, highlighting each publication's key points and weaknesses. The analysis also includes the publication details, MLs, and potential application of selected papers. Additionally, it lists the key parameters of the publications, such as the algorithm, location of wearable, sample size, performance parameters, wearable type, and quantity. A few common problems found during analysis are the availability of data (small sample size), less computing power, energy efficiency, and generalizability.

Thirdly, it suggests the widely used algorithms, wearable sensors, and location for a specific application. Similarly,

it shows the relationship between the sample size by distributing it according to the target application. The paper highlights the need to collect user gait data using optimal sample size to limit data bias and ensure statistical rigour. Lastly, this paper presents some open research challenges for the researchers working in this domain.

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ABDUL SABOOR received the B.S. degree in software engineering (SE) and the M.S. degree in information technology (IT) from the School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan, in 2015 and 2018, respectively. During M.S. degree, his research aims wireless body area networks (WBANSs), sensor networks (SNs), software defined networks (SDNs), and ETSI smartBANs. He has served as a Team Lead for the National Technology Funded Research and Development (R&D) project for one year. He is currently working with the Thomas Johann Seebeck Department of Electronics, School of Information Technology, Tallinn University of Technology. His latest domain of research is the Development and Exploitation of a Smart Wearable-Assistive Neuromuscular Stimulation System Using Data Analytics.



TRIIN KASK received the M.Sc. degree in translational medicine from Helsinki University in 2014. She is currently pursuing the Ph.D. degree (themed Thesis Clinical Assistive Technology for Patients with Neurodegenerative Disease). During her Ph.D. studies, she has developed a mobile application and algorithm for analyzing the human gait patterns and is actively working in developing IT-solutions in E-Health for European and African countries. One conference paper with title Effects of Physical Exercise on Balance, Range of Motion (ROM), and Angular Velocity (AV) Measurements has been presented in XXIV World Congress of Neurology. Her research interests span IoT and the application thereof in the field of medicine.



ALAR KUUSIK (Member, IEEE) received the Ph.D. degree in IT from the Tallinn University of Technology (TalTech), Estonia, in 2001; followed by Postdoctoral program at Tokyo Denki University, Japan. He is currently serves the position of Estonian C/COM/IT joint chapter chair. He has been developing commercial embedded electronic devices for U.S. and European customers and involved with several international research and innovation projects related to smart environment, telecare, and m-health. He has been consulting Estonian government and hospitals in telemedicine topics. He has published more than fifty peer-reviewed articles and owns several patents. At moment, he also serves the position of Senior Researcher and a Lecturer with TalTech, focusing on IoT, biomedical sensorics, and body area networking.



MUHAMMAD MAHTAB ALAM (Senior Member, IEEE) received the M.Sc. degree in electrical engineering from Aalborg University, Denmark, in 2007, and the Ph.D. degree in signal processing and telecommunication from the University of Rennes1 France (INRIA Research Center) in 2013. He joined as Assistant Professor with the Swedish College of Engineering and Technology, Pakistan, in 2013. He did his Postdoctoral Research at the Qatar Mobility Innovation Center, Qatar, from 2014 to 2016. In 2016, he joined as the European Research Area Chair and an Associate Professor with the Thomas Johann Seebeck Department of Electronics, Tallinn University of Technology, where he was elected as a Professor, in 2018. Since 2019, he has been the Communication Systems Research Group Leader. His research focuses on the fields of wireless communications–connectivity, NB-IoT 5G/B5G services and applications, and low-power wearable networks for SmartHealth. He has more than 15 years of combined academic and industrial multinational experiences while working in Denmark, Belgium, France, Qatar, and Estonia. He has several leading roles as a PI in multimillion Euros international projects funded by European Commission (H2020-ICT-2019-3, 951867, NATO-SPS (G5482), Estonian Research Council (PRG424), and Telia industrial grant. He is the author or coauthor of more than 80 research publications. He is actively supervising a number of Ph.D. and postdoctoral researchers. He is also a Contributor in two standardization bodies (ETSI SmartBAN, IEEE-GeenICT-EECH), including Rapporteur of work item: DTR/SmartBAN-0014, Applying SmartBAN MAC (TS 103 325) for various use cases. He is an Associate Editor of IEEE ACCESS JOURNAL.



YANNICK LE MOULLEC (Member, IEEE) received the M.Sc. degree from the Université de Rennes I, France, in 1999, and the Ph.D. and HDR (accreditation to supervise research) degrees from the Université de Bretagne Sud, France, in 2003 and 2016, respectively. From 2003 to 2013, he successively held a Postdoctoral Researcher, an Assistant Professor, and an Associate Professor positions with the Department of Electronic Systems, Aalborg University, Denmark. He then joined with the Thomas Johann Seebeck Department of Electronics, Tallinn University of Technology, Estonia, first as a Senior Researcher, from 2013 to 2016, and as a Professor, since 2017. His research interests include span embedded systems, reconfigurable systems, the IoT, and the application thereof. He has supervised or co-supervised more than 50 M.Sc. students and 11 Ph.D. students. He has been involved in more than 20 projects, including five as PI, co-PI, or co-main applicant; one such notable project was the H2020 COEL ERA-Chair project from 2015 to 2019. He is member of the IEEE Sustainable ICT Technical Community.



IMRAN KHAN NIAZI (Senior Member, IEEE) received the B.Sc. degree in electrical engineering (specialization: biomedical engineering) from Riphah International University, Islamabad, Pakistan, in 2005, and the master's degree in biomedical engineering from University and FH Luebeck, Luebeck, Germany, in 2009, and the Ph.D. degree from the Center of Sensory-Motor Interaction, Health Science Technology Department, University of Aalborg, Aalborg, Denmark, in 2012. After working as a Postdoctoral Researcher for a year, he moved to the New Zealand College of Chiropractic, New Zealand, in 2013, where he is currently working as Senior Research Fellow. His research interests focus on rehabilitation engineering with a patient-centered approach. He is interested in studying and understanding the altered mechanism of motor control and learning in neurological disorder to develop various technologies that can enhance the QOL of these patients.



AHMED ZOHA (Member, IEEE) received the Ph.D. degree in electrical and electronic engineering from the 5G Innovation Centre, University of Surrey, U.K., and the M.Sc. degree in communication engineering from the Chalmers University of Technology, Sweden. He has more than 12 years of experience in the domain of artificial intelligence, big data-enabled self-organizing networks for wireless communication, healthcare technologies, and smart energy monitoring. He is currently a Lecturer with the School of Engineering, University of Glasgow, U.K. His research work is centered around a broad range of machine learning applications spanning 5G network optimization, human behavior modeling for clinical interventions, non-intrusive load monitoring, and he strongly advocates the use of AI for social good. His research has been cited by national and international bodies, regulators, and the media. He has also received the two IEEE best paper awards.



RIZWAN AHMAD (Member, IEEE) received the M.Sc. degree in communication engineering and media technology from the University of Stuttgart, Stuttgart, Germany, in 2004, and the Ph.D. degree in electrical engineering from Victoria University, Melbourne, VIC, Australia, in 2010. From 2010 to 2012, he was a Postdoctoral Research Fellow with Qatar University under the support of a QNRF grant. He is currently an Assistant Professor with the School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan. He has published and served as a reviewer for leading IEEE JOURNALS and conferences. His research interests include medium access control protocols, spectrum and energy efficiency, energy harvesting, and performance analysis for wireless communication and networks. He was a recipient of the prestigious International Postgraduate Research Scholarship from the Australian Government.

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